

**Food Purchasing Behavior and Price Interventions:
How Taxes and Subsidies Affect
Grocery Store Food Choices in a Field Study**

A Thesis

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ABSTRACT

Do price interventions, namely taxes on unhealthy food and subsidies on healthy food, affect food-purchasing behavior? If so, can they be used to improve health? With the intent to better understand these questions as well as the general dynamics between food preference and price, this paper (a) provides a theoretical framework for understanding purchasing behavior of lower income households subject to taxes and subsidies, and (b) estimates the effects of a price intervention by using data from a six-month field experiment where 212 households were randomized into a control or treatment group, where the treatment group faced a 5 percent tax on unhealthy foods and 5 percent subsidy on healthy foods relative to the control group. The theoretical model suggests that price interventions will have different, and sometimes undesirable, effects depending on the individual's preferences, with lower income individuals being more likely to be negatively impacted by a tax. In the empirical model, the combined tax and subsidy had little effect on household purchasing behavior, and did not increase food purchases in important health-related categories such as fruits and vegetables. To policy makers these results suggest that small taxes and subsidies may not help individuals make better, healthier, food choices.

BIOGRAPHICAL SKETCH

Matt McGranaghan earned a Bachelor of Science Degree in Neuroscience from Lafayette College in 2010. He joined the Dyson School of Applied Economics and Management at Cornell University in the fall of 2012. While pursuing his Master's at Cornell, he worked as a Teaching Assistant for four semesters and a summer. After his first year in the program, he received the departments "Outstanding Teaching Assistant Award", in recognition of his abilities and enthusiasm as a TA. In addition to committing himself as a TA, Mr. McGranaghan worked as a research assistant who specialized in data collection and exploratory data analysis. Upon completion of his Masters degree, Mr. McGranaghan will pursue his PhD in the Dyson School at Cornell where he will continue his studies in applied economics, and in particular the intersection between consumer behavior, food, and health.

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INTRODUCTION

Obesity is a growing problem with 69 percent (155 million) of American adults ages 20 and older being overweight and 35 percent (78 million) being obese compared to 66 percent and 30 percent a decade ago (NCHS, 2014). This increase in obesity has been tied to higher rates of many health conditions including cardiovascular disease and Type II diabetes, each of which can carry heavy personal costs and contribute to high societal costs (Go, 2013; Flegal, 2005; Cawley, 2012). Furthermore, while the prevalence – the proportion of a population with a condition – of obesity in the United States has been on the rise, the trends may be most austere for lower socioeconomic groups (Ogden, 2010).

The U.S. government is combating these trends by acting to change the food purchasing and consumption environments of its citizens. For example, the U.S. government has tried improving information (requiring calorie labels on menus), educating consumers (MyPlate.gov), “nudging” people towards healthier foods (Smarter Lunchrooms Movement), banning certain food products (Trans Fats), and using price interventions on various classes of foods (proposed sugar sweetened beverage tax in New York State).

Of these tactics, price interventions such as food taxes and subsidies are receiving considerable attention from both policy makers and media outlets. Despite numerous attempts to identify the effect of such policies, there is not a clear idea as to their actual effect (Allais et al. 2010; Brownell et al, 2009; Clark and Dittrick, 2010; Kim and Kawachi, 2006; Kuchler et al. 2005; Leicester and Windmeijer, 2004; Mytton et al. 2007, 2012; Powell and Chaloupka, 2009). On the simplest level, taxing less healthy foods will increase their price, and a rational consumer who equates marginal utility per dollar will consume less of the taxed food. Taxes on tobacco products have increased over the years on these bases, and have drastically reduced smoking

levels (Chaloupka et al., 2012). However, the dynamics may be more complex for food than they are for tobacco, primarily because individuals need to consume above a minimum threshold (a subsistence level) of calories in order to survive, while they don't need to consume tobacco. Thus an important question is: are fiscal policies for health promotion - taxes on unhealthy foods and subsidies on healthy foods - effective tactics in helping individuals make better food-purchasing decisions? Furthermore, how do these fiscal policies affect people at different income levels? This thesis serves to shine light on these, and related, issues.

This thesis first investigates the interactions between food policies and income by positing a theoretical model for how a low-income and calorie-constrained individual's purchasing behavior will react to fiscal policies. The model suggests that an individual's reaction to a fiscal policy is highly dependent on: the relative prices of foods of healthy and unhealthy food; the individual's preferences for less healthy food, healthy food, and non-food items; and the individuals available budget.

Next this thesis tries to measure the effect of a combined tax on less healthy food and subsidy on healthy food by looking at a field study that gathered food-purchasing data from two grocery stores where customers faced price interventions. Participating households were randomized into a treatment or control group, with the treatment group receiving an effective 5 percent tax on less healthy foods and 5 percent subsidy on healthy foods. In addition to looking at the overall treatment effect, this thesis investigates whether the treatment had a different effect on lower income households. The results indicate few changes in purchasing behavior as measured by various nutritional outcomes, and no positive significant changes in product groups where policy makers would want to see changes such as fruits and vegetables. Despite the finding that small fiscal policies may not have a marked effect on nutritional outcomes, they still

may be viable approach to helping the U.S. population become healthier through a guided reinvestment of revenues into food and health education and research programs.

The rest of this paper is as follows. Section II provides an overview of relevant literature. Section III puts forth a theoretical model based on a hypothetical utility function based on utility from less healthy foods, healthy foods, and a composite good. The model generates predictions about the effects of various fiscal policies on food purchasing behavior. Section IV discusses the experimental design, data collection, and empirical strategy. Section V provides a statistical overview of differences in the data and estimates a set of models that examine the effects of price interventions on healthy and less healthy foods, and how the intervention may have differentially affected lower income households. Section VI concludes.

SECTION II: LITERATURE REVIEW

This literature review begins by discussing obesity and how it relates to human health. It discusses how it is measured, the magnitude to which it has changed over time at the population level, and a few of the societal and economic costs related to obesity. It then segues into how food choice affects obesity, and specifically how food choice is influenced by one's food environment, including a discussion on why the food environment in the United States may be failing its citizens. It expands on that discussion by reviewing various policies that have been put forth to address obesity, with a focus on two fiscal policy instruments that are receiving considerable attention both from academia and the popular media: taxes and subsidies. Lastly, this review looks at how other scholars have tried to model and measure the effects of these fiscal policies have on health.

A. Obesity and Health

Obesity and overweight are labels for “weight relative to height” ranges that are considered unhealthy (NIH, 1998). The label is commonly based off of a measure called Body Mass Index (BMI), where a higher BMI is generally considered less unhealthy, though too low of a BMI can also be deemed unhealthy (NIH, 1998). To calculate BMI, you take a person's weight (in kg) and divide it by the square of their height (in meters). A healthy BMI is indexed from $18.5 - 24.9 \text{ kg/m}^2$, an overweight BMI ranges from $25.0 - 29.9 \text{ kg/m}^2$, and obese BMI refers to a BMI of 30 kg/m^2 or higher. To illustrate, an individual who is 5'9" is considered in the healthy weight range if they weight between 125 lbs. and 168 lbs. The same individual would be considered overweight if they weighed between 169 and 202 lbs., and they would be considered obese if they weigh more than 203 pounds (NIH, 1998). As of 2010, the average BMI

in the United States for males ages 20 years and older was 28.6, and for females it was 28.7 (Fryar, Gu, and Ogden, 2012), both of which occupy the upper portion of the obesity range.

BMI is used as a construct for weight-related healthiness because it correlates highly with an individual's body fat levels, which are highly correlated with an individual's risk for certain diseases and other health-related ailments. Health risks that have been linked to high BMIs include: heart disease and stroke, high blood pressure, diabetes, osteoarthritis, gallbladder disease, sleep apnea, gout, and even some types of cancer, with the problems generally become more severe as BMI increases (National Cancer Institute)¹.

However, while BMI is useful in that it gives health professionals a quick and easily measurable data point for assessing certain health risks, it is limited in its construct validity. Specifically, it does not directly measure body fat, which at increased levels is a core driver of health-related issues. Consequently, it is not the only measure used in accessing health and risk, with others being waist circumferences, waste-to-hip ratio, skinfold thicknesses, bioelectrical impedance, MRI scans, and X-ray absorptiometry (Hu, 2008).

Obesity is nothing new to society; it has always been around to some degree. However, it has been on a sharp rise in the U.S. since the 1970's. In the mid 1970's the prevalence in the U.S. was less than 15 percent. Today it is over 30 percent (FIGURE 1 and FIGURE 2). This sharp uptick in the prevalence of obesity has lead to overweight and obesity becoming the second leading cause of premature death in the U.S., and they are beginning to challenge smoking as the leading cause (Hennekens and Androeotti, 2013).

¹ More accurately, there exists a U shaped relationship between BMI and morality.

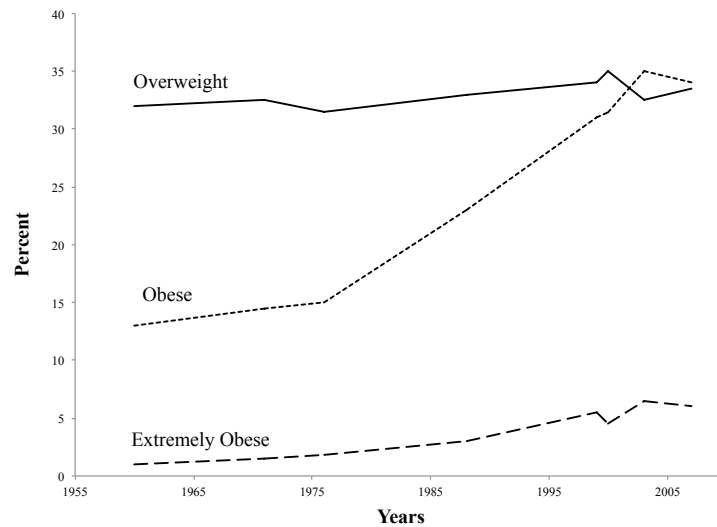


Figure 1: Trends in overweight, obesity, and extreme obesity. The graph is compiled from data from the CDC and shows weight status for adults aged 20-74 years in the U.S. from 1960-2010.

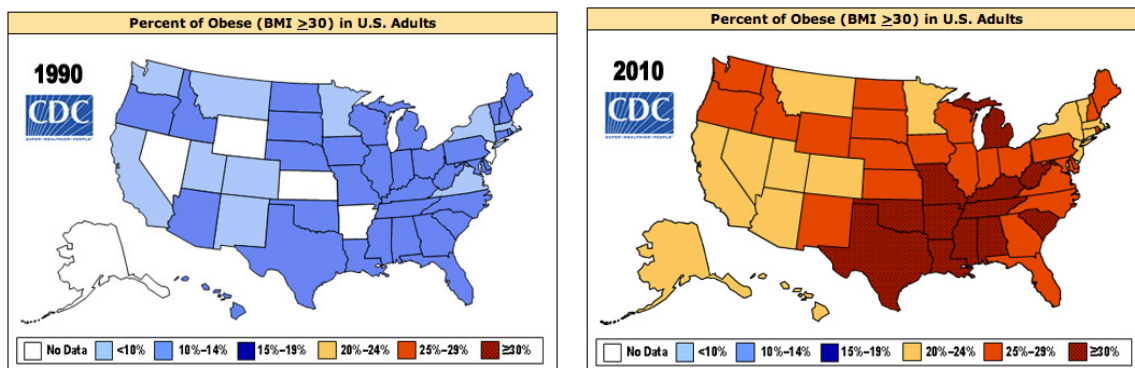


Figure 2: Map of the prevalence of obesity. The graph is compiled from data from the CDC and shows obesity rates in adults aged 20-74 years in 1990 (left) and 2010 (right) in the U.S. The graphs shows that there were no states in 1990 with obesity rates above 15 percent, and that there were no states in 2010 with obesity rates less than 20 percent, indicating a substantial increase in obesity across the entire U.S. population.

B. The Economics of Obesity

Many overweight and obese individuals live long and healthy lives. Still, on the population level, overweight and obesity are associated with greater unhealthiness as well as greater healthcare costs.

In 2006, the estimated incremental costs of treating overweight and obese individuals compared to healthy weight individuals, *ceteris paribus*, were \$147 billion dollars, or 42 percent more per individual (Finkelstein, 2009). The aforementioned study parsed out many of the overweight- and obesity-related diseases and health risks including diabetes and cardiovascular disease, and the combined costs of obesity together with its correlates would be much higher. Specifically, the estimated costs from diabetes were \$174 billion in 2007, and \$312 billion from cardiovascular disease in 2006. Though the diabetes and cardiovascular disease estimates are not mutually exclusive – someone who has diabetes may also have cardiovascular disease – the numbers serve as a humbling indicator of the magnitude of the costs (Go et al, 2013).

A recent quantitative review by Tsai et al. looked at 33 US-based studies that estimated the direct medical costs of obesity. From the 33 studies, Tsai et al. identified four high-quality studies that yielded an estimated incremental cost of \$266 per overweight individual and \$1,723 per obese individual². In addition to looking at the high quality studies, the authors conducted pooled estimates of incremental costs, which came to about \$498 per overweight individual and \$1662 per obese individual, right in line with estimates for the high quality studies. Though the review found significant differences between the medical costs for health and overweight individuals, it also found that costs have not significantly increased (or decreased) over the past decade (Tsai et al, 2013).

These estimates suggest that, at their current levels, overweight and obesity are costly. Despite the news that costs have not increased, it would be naive to think the worst is in the past: the prevalence of obesity has increased over the past four decades and is projected to continue to

² High quality studies were identified as ones that used nationally representative samples, analyzed adults of all ages, used standard BMI cutoffs, and reported cost or expenditures and opposed to charges. Charges are systematically different than costs in that they represent fees from health care providers for a service, while costs represent the actual amount required to provide the service. Therefore, charges may be significantly inflated compared to the actual cost to provide the service.

increase into the future, potentially as high as 50 percent by 2030 (Wang et al, 2011). So while the cost of treating overweight individuals has not significantly increased over the past decade, it has not decreased either, and that means the costs will continue to increase in tandem with increases in prevalence.

On the topmost-level, the U.S. has a general population trend of increasing prevalence, referred to as the incidence rate – the number of new cases between two measurement periods. If we look a little deeper we can see there exists considerable variation in prevalence between different socioeconomic and demographic groups (Wang and Beydoun, 2007). Using data from the National Health and Nutrition Examination Survey (NHANES) and the Behavioral Risk Factor Surveillance Survey (BRFSS) researchers saw a combined overweight and obesity prevalence increased from 47.4 percent to 64.5 percent from 1976-1980 to 1999-2000 and that the incidence rate was similar across groups, about 0.3 - 0.9 percent (Wang and Beydoun, 2007). They also found that different groups had vastly different baseline prevalences, with minority and lower socioeconomic groups being disproportionately affected. These differences between subpopulations, if persistent, suggest there may exist potential systematic biological, socio-cultural, economic, and environmental factors as the core drivers of the difference, including differences in perception of body image, lifestyle, and social and physical environments (Wang and Beydoun, 2007).

C. Food, Health, & Obesity

The issue of obesity, and more generally weight gain, is tractable in the sense that it is an issue of energy balance. If energy in – food intake – is greater than energy out – exercise and metabolism – then the individual is going to store the excess energy and gain weight. Even

though the problem can be boiled down to an imbalance in energy in and energy out, this idea is extremely complex. It is not the result of one factor, but the result of many complex and interacting systemic, environmental, behavioral, and biological factors (Swinburn et al, 2011). Though multidimensional, food is contributing factor, with many believing that the increase in obesity is a consequence of consuming more calories today than we used to consume (Cutler, Glaeser, Shapiro, 2003). Then the question becomes, “What has driven us to consume more calories?”

For much of the 19th and 20th centuries, weights were below the levels thought to be optimal for maximum longevity (Fogel, 1994). Thus in the past, increasing caloric intake was seen as very desirable. Society responded with the Green Revolution – a series of technological advances that drastically increased agricultural production in the developed world, which yielded less expensive calories and healthier (and fuller) families. The cost to produce a calorie continued to decrease over the decades, food products became more processed, food companies became better at marketing their products, and individuals responded by continuing to eat more of them. It is this trend that many believe has led to market failures that contribute to food’s over- and improper- consumption (Freebairn, 2010).

One reason why the current food environment is seen as a broken market is because consumers do not have the nutritional knowledge in order to make the best choices. Furthermore, consumer’s choices are very sensitive to marketing and the individual’s environment, which are not in the individual’s control, and may not be in their best interest (Freebairn, 2010). Consider the case of a child. A child likely does not know what foods are best for him/her. Furthermore, the child is very impressionable – he/she believes the information in front of them (Stead et al, 2003). Now present this child with a colorful and fun advertisement for confectionary, and the

end result is a child who has a preference for sweets. Another reason there may be a market failure is that individuals prioritize immediate gratification over potential long-term negative results, i.e. individual's don't understand the long-term implications of their food choices (Freebairn, 2010). This is the classic case of "indulge today, diet tomorrow". Lastly, there are spillover effects (externalities) in the sense that some of the costs of obesity are borne by society, such as the large government-subsidized health costs mentioned above (Wang et al. 2011).

Taken together, if society, and the individuals who comprise it, believes it is not at a socially optimal level of obesity, and the market cannot correct itself, it would be prudent for regulators to consider formulating public policies that have the potential to counteract the current obesogenic environment and market failures so as to help individuals make decisions more in line with their best interest.

i. Socioeconomic Status

In previous sections I discussed the socioeconomic and demographic disparities in obesity as well as touched on how the food market in the U.S. may be failing the consumers within. Thus, from a welfare standpoint, it is important to understand if (and how) these factors interact. Consider the case of two households, one low-income and another high-income. The households have markedly different incomes that allow them to purchase certain types and quantities of food. However, the lower income group, given their tighter budget constraint, may be limited to a bundle of less healthy food, which negatively affects their overall energy balance, and in turn increases their likelihood of obesity.

Darmon and Drewnowski (2008) discuss these interactions, and in particular how socio-cultural and socioeconomic factors such as cooking skills and the motivation to cook influence

one's food choices. However, they conclude that it is not clear whether these factors contribute to actual difference in diet quality, but rather there might exist mediating factors between socio-cultural characteristics and food choices. For example, assuming it takes more time to prepare a healthy meal compared to an unhealthy one – an exaggerated case would be a home cooked meal from scratch vs. fast food – then individuals with less free time may be naturally inclined towards quicker meals, which may be less healthy. In this simplified example, it is the value of time, not necessarily the preference for healthy or healthy foods that is driving food choices.

In addition to mediating factors, there are direct factors that influence one's willingness and ability to buy healthy foods. One such factor is that healthier foods are generally more expensive, and that higher socioeconomic groups are more likely to eat healthier food groups such as lean meats, fish, whole grains, and fresh fruits and vegetables – foods that are generally more expensive - compared to low socioeconomic status groups (Darmon and Drewnowski, 2005, 2010).

Differences in education and information availability are other reasons that might explain the variation in food choices between individuals of different socioeconomic status (Kereney et al. 2000). Specifically, individuals of higher socioeconomic status may be more able to more accurately identify healthy and unhealthy foods and the long-term costs (and benefits) of consuming unhealthy (and healthy) food. Thus, an individual of lower socioeconomic status who is acting under incomplete information might choose the less expensive option in unhealthy food when they would have chosen the healthy option if they had complete information. However, education and information are not sufficient conditions for behavioral change, as low-SES individuals might have food choices that are bounded by their economic resources.

ii. Obesity Policy

Given the obesity epidemic the U.S. faces, and arguably broken markets that helped develop it (cheap calories, poor information around the health affects of food, and targeted marketing), it is reasonable that policy makers should want to intervene, both on the behalf of the population, and on behalf of its own financial stability.

The first step to improving this situation is developing a better understanding of the scope, scale, and details of the problem as well as which policy mechanisms are most effective in influencing behavior in the desired direction. Koplan et al. (2005) put forth a plan of action that talks extensively on types of policies that currently, or could potentially, have an impact on obesity in the US. The report talks about six major policy areas: (1) Research and Evaluation, (2) Surveillance and Monitoring, (3) Nutrition and Physical Assistance Programs, (4) Nutrition Assistance Programs, and (5) Agricultural Policies, and (6) and Other, which mainly focused on food taxes and subsidies.

The first two topics focus on the fact that a better understanding is needed of the epidemic. What are the optimal measures for preventing it? What high-risk groups are most affected by it? One of the best ways to answer these questions is to conduct and support good experimental research, which can help researchers make causal claims about changes in dietary and physical activity behaviors on healthy related outcomes. In addition to better understanding the causes, a better understanding is needed of the effects, specifically the social, economic, and medical consequences of obesity. Researchers have gained tremendous ground on this front over the past two decades, but by no means have a complete understanding of it. Only with more, and better data, will researchers be able to disentangle the myriad of contributing factors: biology; physical activity; nutrition; and social, environmental, and behavioral risk factors. Regardless of

the complexity of the problem, better data and analytics are essential if we want to learn the subtleties in the data (Koplan et al., 2005).

The third and fourth major policy topics are Nutrition and Physical Activity Programs and Nutrition Assistance Programs. These policy topics are designed to educate individuals on healthy food, improve food access, improve dietary quality, and to alleviate hunger. Around one in five Americans participates in one or more of these programs, which include: the Expanded Food and Nutrition Education Program (EFNEP); the Supplemental Nutrition Assistance Program (SNAP); the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC); and the Child Nutrition Programs (USDA, 2003). For many of these programs, such as SNAP and WIC, there are not specific guidelines as to what products recipients may receive with their benefits. However, given recent conversations connection between federal nutrition assistance and obesity (Dinour, Bergen, and Yeh, 2007), some argue that these programs should also focus on important factors such as obesity prevention, enabling access to healthy dietary choices, and exploring new and innovative pilot programs that encourage healthy eating and healthful behaviors. Furthermore, in order for these programs to be effective, they need to be evidence based, keep in mind high-risk populations, and deliver consistent messages (Koplan et al, 2005).

Another major set of policies that affect the obesity epidemic is Agricultural Policies. The emphasis here what a country grows, and provide incentives (subsidies) to grow, should be congruent with the nutritional goals of the country, and should not apply negative forces on the types and quantities of foods available to children and families in the federal food assistance programs. One area of concern is that the price of calorie-dense, processed and prepared foods (fast food) has decreased faster than the price for less calorie-dense foods (e.g. fruits and

vegetables). In this scenario, the rational consumer equating marginal utility per dollar will shift a greater proportion of their consumption to the more calorie dense, and presumably less healthy products (Finkelstein et al., 2005).

The last major policy instrument is fiscal interventions, specifically taxes and subsidies.

Food Taxes

Food taxes, just like any other tax, are additional financial charges imposed on a buyer (or buyers) at some point between the supplier and end consumer. Taxes may be levied at different levels of the supply chain, but are most commonly seen at the wholesale or retail levels. Taxes can take on multiple forms including such as a fixed tax per volume or a percentage of the purchase price. Taxes in the discussion of obesity policy have primarily been put forth as a way to curb the consumption of certain unhealthy food products by increasing the price, and thus decreasing the demand, of those products. To illustrate, consider again the rational consumer who has decreasing marginal utility and equates marginal utility per dollar across his/her purchases. Increasing the price will decrease the marginal utility per dollar the individual receives. Thus, the individual will reduce consumption (increasing marginal utility) in order to re-align marginal utility per dollar with the remainder of their consumption.

The three most well known types of taxes are excise taxes, value-added taxes (VAT), and sales taxes. An excise tax is a tax on a particular good that is paid by the producer or retailer. In many cases these taxes are not salient to consumers; such is the case with gasoline and alcohol. A sales tax is one that is collected from the buyer at the point of purchase. A value added tax (VAT) is one that is levied on a good *ad valorem*, or “according to the value”. For clarification, most value added taxes are imposed on the *added value* from the transaction whereas sales taxes are levied on the *total value* of the transaction.

Taxing is just one way to increase the price of a food product. Another way is to change the exemption status of a product with respect to a certain tax. For example, if the status quo is to exempt all food items from a particular VAT, a governing body could effectively increase the price of a particular food by taking away the tax exemption on certain products. Many countries such as United Kingdom do these sorts of tax exemptions with products such as alcohol and confectionary. The end result is essentially the same as taxing certain products.

Beyond the type of tax, there are different dimensions, or characteristics, of a product that can be taxed. A tax may be implemented based on the underlying nutritional content of the food such as saturated fat, sweeteners (natural, artificial, or both), or salt, just to name a few. Another way to tax food would be to tax it based on a healthiness score (or index). Some examples of health indices include the Guiding Stars Program, WXYfm, the SAIN,LIM system, and SSCg3d score which each create an index from the underlying macro and micronutrients in a particular food and assign the food a score. Furthermore, a governing body could instead impose a tax on entire food groups such as sugar-sweetened beverages, confectionary, or any other food category.

Taxes, like most market-influencing interventions, have their drawbacks and benefits. One reason food taxes are generally disliked is because they raise the price of a good. Take for example a healthy individual who occasionally drinks a soda (a food that many want taxed). They might be upset by having to pay a higher price for a product that they consume responsibly.

Another reason food taxes are disliked is because they can be regressive – they impact lower income households' more than higher income households. This happens for a few reasons in the case of food. Firstly, lower income households spend a larger proportion of their total

expenditures on food (Engel's Law), which means a tax on food will be disproportionately felt by lower income households compared to higher income households. Secondly, lower-income households buy relatively more of the foods that would be classified as "unhealthy", which means not only is a greater proportion of the total budget allocated to food, but also a greater proportion of the food budget would be taxed (Darmon and Drewnowski, 2005). The regressive nature of a food tax can have ill intended consequences. The end result is that lower income household's food bill increases a disproportionate amount compared to higher income households when facing a tax.

Despite their shortcomings, taxes are attractive for many reasons. Firstly, they don't require substantial infrastructure or costs on the government side. All that is needed is an algorithm to identify which products should be taxed and how they should be taxed, and a system for monitoring and collecting the taxes. Another reason taxes are attractive is that they might be able to lead to better nutritional outcomes through reduced consumption of taxed foods. Finally, taxes can be source of revenue that can be invested in obesity and related health issues. Revenues can be channeled into healthcare, health education and outreach, or research programs (Leicester and Windmeijer, 2004; Brownell et al. 2009; Mytton et al. 2012; Kuchler et al. 2005; Kim and Kawachi, 2006; Powell and Chaloupka, 2009).

An important factor about taxes are only effective in reducing the amount of taxed food consumed if they have negative own price elasticities, i.e. the demand for a food decreases as its price increases. This may not always be the case for certain subsets of the population. Jensen and Miller (2008) show that when the price of a staple (necessary food) increases, Chinese households in a subsistence zone – a level of consumption where they struggle to consume a minimum amount of calories –will actually devote more of their budget to it, despite the higher

price. A parallel can be made between lower income households in the U.S. There may be lower income households who are in a “subsistence zone” of their own and can only afford to buy very inexpensive (and potentially less healthy) calories. All a tax would do for these individuals would be to put their food budgets under more duress, as it is not feasible for them to switch to healthy foods that are not affordable.

As for the form of the tax, there is no consensus, though good cases have been made for excise taxes over other taxes that are levied as a percentage of the consumer price. One reason why excise taxes may be more effective than sales taxes in reducing consumption is because the latter do not scale linearly with volume. As the volume of a product increases, the price/volume decreases, and individuals may respond to a sales tax by substituting towards higher volume, lower price per volume, containers. Alternatively, buyers may just switch to lower-price brands, resulting in a lower price per volume. Furthermore, excise taxes may be more favorable compared to sales taxes because sales taxes are only seen at the time of purchase, which would pose a problem for certain products such as fountain drinks that can be refilled for free after the initial purchase (Brownell et al. 2009). Furthermore, an excise tax on producers or wholesalers would be easier to collect and enforce since the tax collection is less decentralized, i.e. fewer parties are involved.

Even if a tax does not directly change purchasing and consumption behavior, a positive outcome can result. If the tax does not significantly change consumer behavior, which would be consistent with studies finding low price-elasticities, then the government stands to collect a millions, or even billions, of dollars a year which it can use to fund research, information programs, and subsidize health care costs (Jacobson and Brownell, 2000).

Food Subsidies

Subsidies are different kinds of financial support that reduce prices with the goal of incentivizing better outcomes. A commonly proposed subsidy would be for the government to provide monetary incentives to be used for the purchase of healthy foods, thus reducing the price of healthy foods relative to unhealthy foods.

One primary reason in favor of subsidies over taxes is because, unlike taxes, subsidies don't restrict the consumer's choice set. An individual who faces a new subsidy on a product can still buy the same bundle of products they bought pre-subsidy, more if their old bundle included the now subsidized product. If the same individual faced a tax, they would only be able to buy the same bundle if their old bundle did not include the now taxed product.

On the other hand, while taxes have the potential to be revenue generating, the same cannot be said about subsidies in the short term. Subsidy programs need to be properly funded in order to support their payouts. Despite their short-term costs, in the long term they have the potential to be cost saving if the subsidy payouts are less than health care savings.

Lastly, even if a government successfully sets up a subsidy program, it may have unintended consequences. Lab studies investigating the effects of subsidies on food purchasing behavior have found that some consumers will re-invest the money saved from a subsidy on healthy food on more food in general, which in some ways negates the intended effect of the subsidy (Epstein et al, 2010). Despite those discouraging findings, there is currently a large-scale effort by the USDA to better understand the effects of a targeted subsidy on fruits and vegetables, called the Healthy Incentives Pilot (HIP). The pilot is being evaluated using a rigorous research design including randomized assignment of about 55,000 households in treatment and control groups to assess the impact of a \$0.30 subsidy on targeted fruits and

vegetables on consumption and other key measures of dietary impact. The program was designed to provide an estimate of the federal, state, and local administrative and benefit costs of such a program. Preliminary results from the program indicate adult HIP participants consumed 0.22 cup-equivalents more (24% higher) of target fruits and vegetables than control-group SNAP participants. The estimates are in line with elasticity estimates for fruits and vegetables (USDA, 2013).

iii. Extant Research

Many researchers have taken to understanding the effects taxes and subsidies of different forms would have on health-related outcomes. One way researchers have sought to better outcomes is by looking comparing population-level average purchasing data with price elasticity estimates (Kuchler, Tegene, and Harris, 2005). The authors used ACNielsen Homescan data to estimate own- and cross- price elasticities for U.S. households to investigate the effects of ad valorem taxes on food purchasing behavior. They found that the impact of a large-scale tax would have a small impact on dietary quality, and that the effects would be negligible at lower tax rates. If taxes were earmarked for funding information programs, as several proponents suggest, taxes have the potential to generate a revenue stream the public health community could use for nutrition education. Along very similar lines, Mytton et al. 2006 looked at the effect of a Value Added Tax (VAT) of 17%. Using expenditure and elasticity values from the UK's National Food Survey in 2000, they estimated population effects of different VAT tax schemes. Overall, they found that VAT could be used to produce small, but meaningful, changes in population health. However they also found that, no matter the tax, food expenditures would also significantly increase as a result of the taxing schemes. Another study using the same data but

different nutrient score (the WXYfm³) found similar results: taxing food based on nutritional content was economically regressive - expenditures for lower-income groups increased more relative to the higher income groups (Nnoaham et al 2009).

One important drawback to note in regard to these studies is that it is difficult to extrapolate price elasticities well beyond the prices from which they were derived. Changes in food expenditure, and the own- and cross-price elasticities that are reflections of those change, may not be linear. Thus estimated food expenditures as a result of a tax may not be true to how individuals actually behave.

In addition to the top-down approach mentioned above, many researchers have conducted lab and field experiments in order to investigate how consumers will react to various food taxes and subsidies. Tax/Subsidy experiments have been conducted in numerous environments, from university labs, to school cafeterias, workplaces, and even grocery stores, with the list constantly expanding. Two studies manipulated the prices of low fat snacks in university vending machines and found in both that 50 percent lower prices (subsidies) on low-fat snack sales translated into more than a 90 percent increase in sales of those products (French et al. 1997, 2001). In the case of school cafeterias, a 50 percent reduction in cafeteria prices of fruit and salad led to a quadrupling of fruit sales, but no increase in salad sales (French, et al. 1997). A similar study conducted in a university office cafeteria found that a 50 percent price reduction in the building's cafeteria prices of fruit and salad led to a threefold increase in fruit and salad sales (Jeffery et al. 1994). As for grocery stores, a randomized control trial was conducted in eight supermarkets where over 1000 shoppers were assigned to one of four treatment groups. One of the main

³ The WXYfm nutrient profiling model was developed for use in regulating broadcast advertising of unhealthy foods to children. It rates individual foods on a scale from -15 (most healthy) to +40 (least healthy) based on: energy, saturated fat, total sugars, sodium, protein, fiber and fruit/vegetable/nut content per 100 g.

findings was that households who were randomly assigned to receive 12.5 percent discounts on predefined healthy food bought 11 percent more healthy food during intervention period compared to households that did not receive a discount (Ni Mhurchu et al. 2009). Together, these studies suggest possible benefits of subsidies.

Another way the relationship between price and food has been investigated is by using linear and non-linear optimization routines to look at “optimal” diets. In one study, “Optimal diets” were constructed by picking an optimal bundle of foods from a database of food and nutrition information that minimized cost while still meeting minimum dietary requirements as well as minimizing changes from normal consumption patterns. Looking at the optimality conditions of the optimal diet problem revealed that tightening the budget constraint results in the optimal bundle having more calorie dense foods including more cereals, fats, and sweets (Darmon et al. 2002). Thus, according to this model, the optimal diet for a lower-income individual – one who faces a tighter budget constraint – will include more foods that are generally considered unhealthy, and thus may put them at higher risk of obesity.

iv. Taxes Around the World

Food taxes and subsidies around the world have been introduced with a mix reception. In the United States, many states already have sales taxes or other specific taxes for food. Some states, such as Arkansas, generate tens of millions of dollars a year, and appropriate the revenues to Medicaid, but most states do not have such policies (Jacobson and Brownell 2000). Recently New York City, pursued to ban on sugar sweetened beverages, but a New York State judge ruled against it and the ban was overturned a day before it was to go into affect.

Outside the US, countries such as Norway and Samoa, a small pacific island, have had taxes on sugary beverages and confectionary since the 1980's (Boseley, 2013). Australia has had a 10% tax on sugary drinks, confectionary, and bakery products since the early 2000's. Tonga, an Island in the South Pacific near Samoa and currently the most overweight country in the world, is looking to expand its "unhealthy choices" tax in order to combat its obesity problem. In 2013, Mexico, in order to combat its 32.8 percent adult obesity rate, began taxing food with more than 275 calories per 100g at a rate of 8 percent, and sugary drink at one peso per liter. Hungry also recently enacted a fat tax in order to combat their 18.8 percent obesity rate, which is 3 percent higher than the European Union's average. The Danish set up a tax on foods high in saturated fat such as bacon and butter, and was received so poorly that the tax was rescinded after six months. There were cases of Danes crossing borders in order to stock up on the taxed goods, thus completely circumventing the tax and any benefits it might have for the countries population (Boseley, 2013; Cheney, 2013; The Huffington Post, 2014; ABC Radio Australia, 2014; Time.com, 2014).

v. Considerations

One should be careful when interpreting changes in food purchasing behavior as a result of a price change because other, non-food related behavior might change in the direction that does not benefit overall health. For example, consumers might substitute exercise equipment for snack foods or partake in other unhealthy foods and behaviors (Kuchler et al., 2005)

One of the consistent limitations for the population-level studies that that there is a problem with looking at the effect prices have on weight and nutrition outcomes because price may be an indicator of local competition. Prices may be lower in some areas because of greater

food store availability; thus, the driver of a change in weight-related outcomes may be the result of greater availability *and* lower price, and not necessarily lower prices alone.

Another important consideration is that most price intervention policies, and especially taxes, will likely face pressure from the general public, special interest groups, and affected industries. There have already been example of consider pushback from snack and soft drink products. For example, in light of New York City's former Mayor, Michael Bloomberg's proposed tax on sugar-sweetened beverages, PepsiCo Inc. threatened to move its bottling facility from Westchester NY to Connecticut (Hakim and McGeehan, 2009).

Something else to consider is how tobacco policy relate to food policy of today. Though similar in some respects, there are a couple key differences between food and tobacco products. One, a tobacco product is much easier to define than an unhealthy or healthy product. A tobacco product is one that has tobacco in it, where as there are numerous dimensions on which you can tax food (see discussion above). Second, tobacco products are clearly harmful and have been repeatedly connected to cancer development and early mortality (Doll et al. 1994), whereas the direct connections between food and health are less clear and intensely debated. Lastly, tobacco products are much easier to tax; there are fewer producers, fewer products, and fewer modes of consumption. Still, if policy makers are serious about taxing certain foods, there is much to learn about how the tobacco policies were implemented. Firstly, as evident by the tobacco industry, those in favor of food taxes can certainly expect significant push back from whatever industries are negatively affected as the result of any price intervention. Also, we can learn something about the demographics that were affected. Many people argued against tobacco taxes because they would be regressive for low-income individuals. Implementing support programs, tobacco

control programs, which include educational, regulatory, and clinical programs combated this argument.

Food is just one of many pieces in the big puzzle that is obesity, but it is none-the-less an area that can be focused on to produce meaningful changes in population health, a thus worth investigating. One way to better understand the how differences in food-related behaviors can lead to different health outcomes is through economic models. Economic models can provide an instructive framework for understanding the dynamics between food choice and price, and help develop hypothesis that can be tested in the real world.

SECTION III: THEORETICAL MODEL

The economic view of individual health is that individuals are involved in the production of their own health. Specifically, individuals combine a limited amount of resources – money, energy, and time – in an optimal balance in order to achieve the best outcomes.

Previous economic models have provided insight into how marginal utility derived from various activities has changed over the years, and how these changes have played a role in increasing obesity. A common conclusion of these models is that individuals have rationally decided to accept a higher body weight in exchange for the utility associated with more time spent eating and relaxing (Philipson and Posner, 1999; Cawley, 2004). However, they fall short by not taking into account the fact that individuals need to consume a minimum amount of calories in order to sustain themselves, and that such a constraint strongly influences behavior in certain directions depending on the price of foods and preferences of the individual.

In order to shine line on these dynamics, I develop a mathematical framework for food choice where individuals seek to maximize utility from healthy food, unhealthy food, and a composite good, which constitutes all other goods, under a budget as well as a minimum calorie constraint. By incorporating different types of food products, namely healthy and unhealthy, and making assumptions about their respective prices, I can look at how the their balance of these three groups of products changes in light of different changes in price.

A. Model

In this model, individuals seek to maximize the following utility function:

$$\max U(c, \gamma, x)$$

subject to:

$$c \geq K$$

$$c\gamma(p_h + \tau) + c(\gamma - 1)(p_l + t) + x \leq w$$

Where c is total calories (the amount of food), γ is the percentage of food purchased that is healthy (ranging from 0 to 1), x is a composite good (money not spent on food), w is a budget constraint. p_h and p_l are the base prices for healthy and unhealthy food respectively, and τ and t are price changes (taxes if positive, subsidies if negative) on the different food types⁴. The price of the composite good is normalized to one. In addition to the standard budget constraint there is also a calorie constraint, K , which embodies a minimal level of calories that an individual needs to sustain himself/herself. This is a simplified model of a complex decision making process that essentially treats the individual as a firm that is looking to produce the maximum amount of utility for themselves.

In order to make the model tractable I use a general form of a three good Cobb-Douglas production function, where the individual decides the amount of calories, the percentage of those calories that are healthy, and a level of the composite good.

Equation 1: Hypothesized utility function from Food and non-food Consumption

$$U(c, \gamma, x) = (c\gamma)^\alpha (c(\gamma - 1))^\beta x$$

The variables are the same as before, with the addition of α and β , which can be interpreted as a preference for a particular source of calories. $\alpha + \beta$ is constrained to be less than one, as individuals exhibit decreasing returns to scale for food. If an individual has a very high α relative

⁴ Another way to think about the structure of this model is that the individual is selecting calories from healthy and unhealthy foods separately, where the amount of healthy food is equal to $(c\gamma)$ and the amount of unhealthy food is equal to $(c(1 - \gamma))$. The reason I went with the current formulation is the ease to which it lends itself to visual interpretation. Never-the-less, the formulation does not affect the final results.

β that would mean that a calorie of healthy food translates more readily into utility than a calorie from less healthy food. Due to decreasing marginal utility of healthy and unhealthy food, food purchases (calories) in this model occupy a decreasing proportion of the total expenditures of the household, which is consistent with Engel's law.

B. Calorie Constraint

In the scenario where there the individual only faces a budget constraint, there always exists an optimal balance between total amount of calories (c), the percentage of healthy calories of all calories (γ), and the composite good (x) that will maximize their utility. Furthermore, this optimal balance will be achieved when the marginal utility per dollar is equal across healthy foods, less healthy foods, and the composite good. Thus, when the price of any of these goods changes, consumption will rebalance so as to equate marginal utility per dollar (FIGURE 3).

However, it might be the case this “optimal” amount of calories in the budget-constrained model is below a minimal calorie threshold – the minimum amount of calories ones needs to survive. Upon imposing the calorie constraint, the individual would be forced to buy a greater than previously optimal level of food, as well as less than previously optimal level of composite goods (FIGURE 4). One could imagine such is the case for the food-insecure where the individual consumed food for sustenance even though they would rather be spending it elsewhere, such as investing in their human capital or recreation.

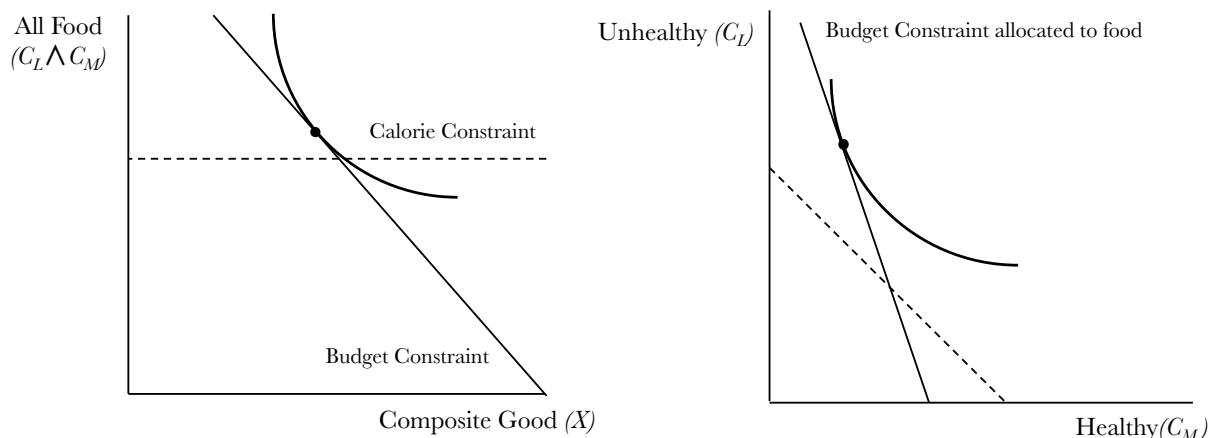


Figure 3: Optimal Bundle for higher income individuals. The left graph shows all food purchases (calories from healthy and calories from less healthy) on the vertical axis, and composite good purchases along the horizontal axis. The right graph shows calories from less healthy on the vertical axis and calories from (more) healthy on the horizontal axis. In both graphs it is clear that the individual's optimal bundle – the point at which the indifference curve is tangent to the budget constraint – is above the calorie constraint.

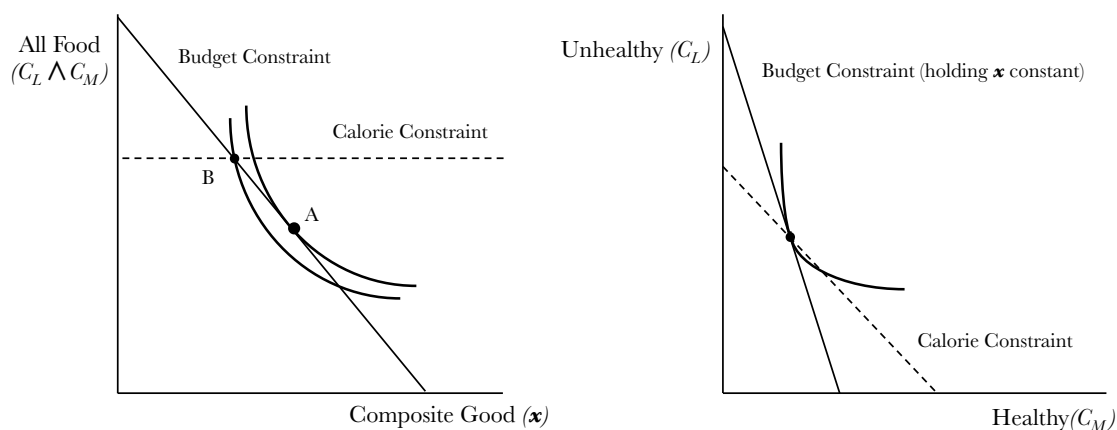


Figure 4: Optimal Bundle for lower income individuals. The left graph shows all food purchases (calories from healthy and calories from less healthy) on the vertical axis, and composite good purchases along the horizontal axis. The right graph shows calories from less healthy on the vertical axis and calories from (more) healthy on the horizontal axis. As evident in the graph on the left, the optimal level of calories for lower income individuals is below the calorie constraint. Since the optimal level (the level producing

the highest utility) is below the calorie constraint, lower income individuals will end up at a corner solution with reduced utility (an isocline shifted down and to the left).

The crux is that is that behavior of the calorie constrained, and other individuals who spend a large proportion of their budgets on food out of necessity rather than preference, is very important to keep in mind when designing policy because these individuals and households have the least amount of flexibility in their buying behavior.

C. Welfare Effects

Next I use this model to estimate the effects of various fiscal policies on food purchasing behavior by using comparative statics analysis, which show what happens to the level of different choice variables in the model (total calories, the percentage of calories that are healthy, the a level of composite good) under changes to the exogenous tax and subsidy parameters that modulate the price of healthy and unhealthy food.

Firstly, the individual can be in one of two circumstances: Lower Income or Higher Income. Higher Income households are ones whose optimal level of calories (c) is above the minimum calorie threshold (K) (FIGURE 3). Lower Income households are households whose optimal amount of calories is not above the minimum calorie threshold (FIGURE 4). Since the preferred level of calories is unattainable, the household has to reduce their consumption of the composite good (x), increase their level of calories (c), and potentially change the composition of healthy and unhealthy foods (y) in order to meet the minimum calorie constraint. The end result will be a lower level of utility than otherwise preferred if no calorie constraint existed.

This is done in the model by introducing a Karush-Kuhn-Tucker multiplier ϕ . If there is slack, the household is of the Higher Income type and their optimal amount of food is greater

than the sustenance level, K , then the corresponding KKT multiplier ϕ is zero – it is not binding. Otherwise, the household is of the Lower Income type, which means their optimal level is less than the minimum threshold and the constraint binds. In this case the KKT multiplier represents a marginal loss in utility of having to consume an additional calorie. The last piece of the model is μ , the multiplier that embodies the shadow price on the budget constraint, which, at optimality, equals the marginal utility of an additional dollar of income. The final version of the model is as follows:

Equation 2: Lagrangian formulation of utility function

$$\begin{aligned} \mathcal{L}(c, \gamma, x, \mu, \phi) \\ = x(c - c\gamma)^\beta (c\gamma)^\alpha + \mu(w - c\gamma(p_h + \tau) - c(1 - \gamma)(p_l + t) - x) + \phi(K - c) \end{aligned}$$

Lets first consider the case of a subsidy on healthy foods. When subsidizing the price of any food, the choice set is strictly increasing, and thus the individual making the choice will be de-facto better off from the utility maximization point of view. Because the subsidy decreased the effective price of one type of good without doing anything to the prices of other goods, the individual could still buy the same level of healthy, unhealthy, and composite good as before the tax.

High-income individuals, those who are above the minimum threshold, will simply rebalance marginal utility per dollar across healthy, unhealthy, and the composite good. Since the effective price of healthy foods decreases, this means that a subsidy will increase the total amount of calories an individual purchases from healthy foods, but it also means the individual increase their total calories from unhealthy foods, a phenomenon which has been observed in lab

settings (Epstein, 2010). Furthermore, whether or not the individual switches to a greater percentage of healthy foods before the subsidy depends the individual's preferences. Specifically, the change depends on how the price change affects the simultaneous substitution of three goods. The essence of the analysis is that the individual will switch to a greater percentage of healthy food if the combined effects of (a) the income effect – the change in the optimal bundle as a result of the individual having a less constrained budget, and (b) the substitution effect – the effect of changing the relative prices between healthy and unhealthy foods – is positive. Similarly to the case for the switch between healthy and unhealthy foods, the individual will increase total calories purchased if the combined effects of the income and substitution effects between calories and the composite good, is positive. These analyses are simplifications, but are useful in that they tell the core story of the dynamics between the three choice variables.

For calorie-poor, Lower Income individuals, introducing (or increasing) the level of subsidy, τ , of healthy foods results in no change in the amount of food purchased, so long as the non-calorie-constrained optimal amount of calories is below the minimum calorie threshold, K . Similarly to the case for Higher Income individuals, the effect a subsidy will have on Lower Income individuals depends on that individual's preferences. However, as discussed before, Lower Income individuals are calorie-constrained, and thus amount of calories does not change from pre- to post-subsidy. The fact that calories remains constant allows a much cleaner picture in the dynamics between the three choice variables, which are embodied in the following figures.

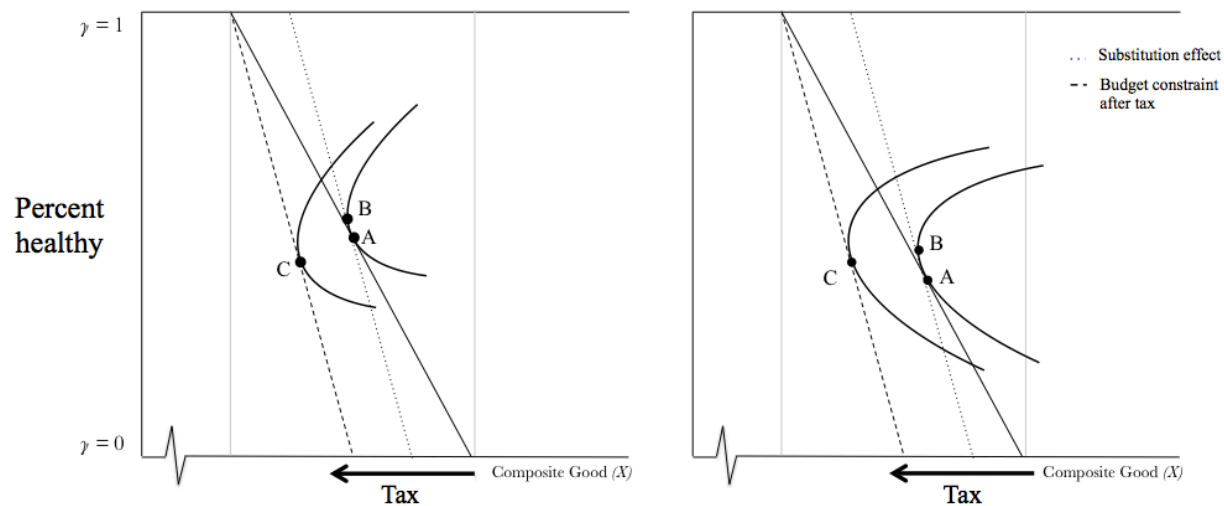


Figure 5: Effect of a tax on lower income individuals. The tax is embodied as a change in slope of the budget constraint. The graph on the left illustrates that a lower income individual who prefers unhealthy food (the individual is less willing to substitute away from unhealthy calories) will decrease their percentage of calories from healthy food. The right graph illustrates the outcome for an individual who prefers healthy food. Specifically, that they will increase their proportion of calories from healthy food.

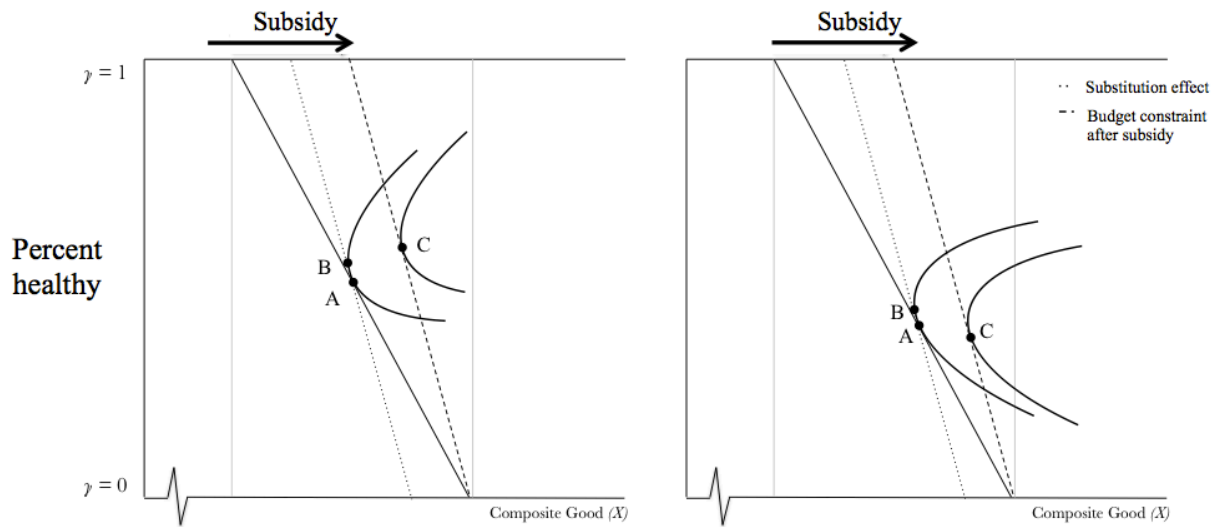


Figure 6: Effect of a subsidy on lower income individuals. The subsidy is embodied as a change in slope of the budget constraint. The graph on the left illustrates that a lower income individual who prefers unhealthy food (the individual is less willing to substitute away from unhealthy calories) will decrease their percentage of calories from healthy food. The right graph illustrates the outcome for an individual who prefers healthy food.

FIGURE 5 and FIGURE 6 summarize the dynamics between γ , x , and utility (remember c is constant) with respect to price changes as the result of taxes and subsidies. The composite good, x , is on the horizontal axis, and the percentage of calories that come from healthy food is on the vertical axis with 0 percent healthy (100 percent unhealthy) at the bottom and 100 percent healthy (0 percent unhealthy) at the top. It is assumed that that unhealthy foods are less expensive than healthy foods, which is consistent with general trends in the prices of healthy and unhealthy foods (Darmon and Drewnowski, 2008). This relationship can be inferred by the budget constraint sloping down and to the right as the quantity of x increases (the household can afford more x if they were to consume all unhealthy calories than if it consumed all healthy).

Furthermore, the tradeoff is linear, as the price difference between healthy and unhealthy calories always remains the same.

These examples reflect the comparative static for a change in γ with respect to a change in the price of less healthy and more healthy calories; a change that policy makers are very interested in. FIGURE 5 refers to a tax on unhealthy calories and FIGURE 6 refers to a subsidy on healthy calories. In both figures, the individual starts out at point A (pre price intervention) and ends up at point C (post price intervention). The movement between point A and point B represents the substitution effect, and the movement between points B and C represents the income effect.

In both the tax and the subsidy scenarios, it is clear that the overall effect on the percentage of healthy food, γ , depends on the shape of the individual's preference for healthy and unhealthy food⁵. If the individual has a strong preference for unhealthy food (left box of FIGURE 5), then a tax on unhealthy food will actually increase the percentage of unhealthy food that individual buys. On the other hand, if the individual has a preference for healthy foods, a tax on unhealthy may result in them switching to a larger percentage of healthy calories. An important aspect to note for the tax scenario is that the lower income individual will always buy less of the composite good, x , regardless of the Lower Income individuals preferences for healthy and unhealthy food.

In this calorie constrained model, the direction of the change in γ depends on the relationship between the marginal utility with respect to γ , $\left(\frac{\partial U(\cdot)}{\partial \gamma}\right)$, the current level of γ , and μ , the shadow price on the budget constraint, or how much the individual's utility would increase if

⁵ You can infer the relative preferences of the individual by the slope of the indifference curve. In the case of a tax, if the level of x decreases faster as you decrease γ compared to an increase in γ , that means that the individual needs to be compensated more for that change, and thus the individual prefers unhealthy food.

the budget constraint was relaxed. In the case of a tax, the change in γ comes down to whether the substituting between less and healthy and more healthy, captured by $\left(\frac{\partial u(\cdot)}{\partial \gamma}(\mathbf{1} - \gamma)\right)$, is greater than the effect of relaxing the budget constraint, μ . If the above expression is positive, the individual will consume a greater percentage of calories from healthy food (right box of FIGURE 5). This relationship, embodied in the shape of the indifference curves, is governed by the prices of healthy and less healthy foods, and the individual's preferences for healthy and unhealthy food. An important feature to note is that as income decreases, the value of an additional dollar in the budget constraint, μ , increases. One way to interpret this result is that the likelihood of the tax having a positive, and desirable, effect on purchasing decreases with increasing severity of poverty.

To elucidate the possible outcomes of a tax on lower income individuals, consider two individuals: Allen and Bob. Allen and Bob each face a tax on unhealthy foods such that the taxed price for unhealthy foods is above what it used to be, but is still below the price of healthy foods. Furthermore, Allen has a relatively strong preference for unhealthy food, and Bob has a relatively stronger preference for healthy food. Since Allen prefers less healthy food, he would rather pay the higher price on unhealthy food than switch to healthy food. Furthermore, because he is paying more for unhealthy foods, he will have to reduce his consumption of the composite good and/or reduce his consumption of the healthy food. If he has relatively inelastic preferences toward the composite good – he prefers spending the money on something besides food – he will end up buying more calories from unhealthy food. On the other hand, Bob, who prefers healthy, doesn't think the unhealthy calories are worth the new price he has to pay for them, and he will increase the proportion of calories from healthy food. In Allen's case, the income effect

dominates, whereas in Bob's case, the substitution effect dominates. Even though both Allen and Bob are rational in their responses to the tax, their outcomes differ considerably.

D. Giffen Behavior

One of the surprising, yet intuitive results is that some lower income individuals with strong preferences for unhealthy goods will increase the proportion of unhealthy foods in light of a tax. This behavior suggests upward sloping demand and the existence of Giffen goods.

Interestingly, this behavior has been discussed in the context of extremely poor households in two provinces in China (Jensen and Miller, 2007). In their paper, Jensen and Miller discuss a similar non-willingness to substitute away from certain staple products when faced with extreme poverty and subsistence concerns (FIGURE 7). To investigate whether this behavior actually exists in the real world they look at how price subsidies affect the demand for dietary staples in extremely poor households in two provinces in China. They found strong evidence for upward sloping demand for rice in extremely poor households in the Hunan province, and weaker evidence for wheat in the Gansu province. Furthermore, they find that the degree of this behavior is largely a function of the severity of the household's poverty.

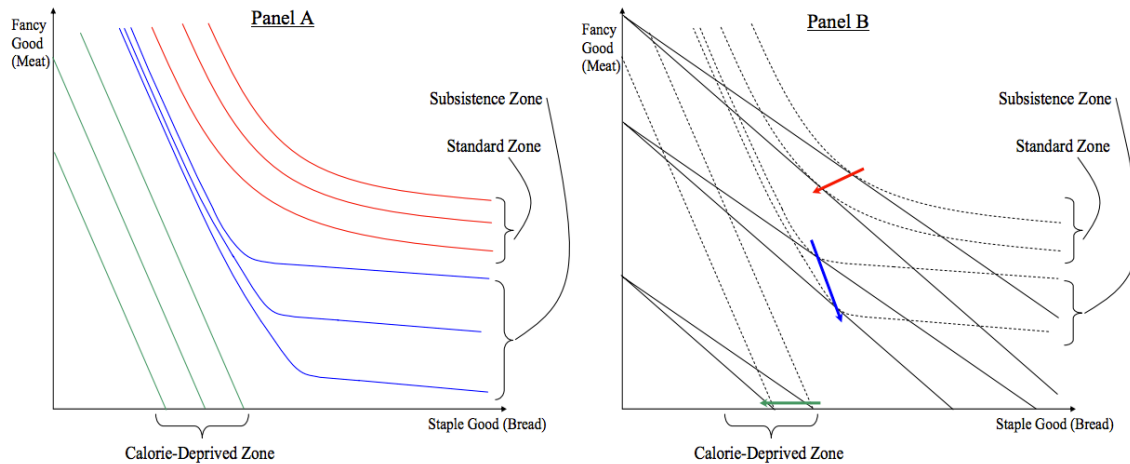


Figure 7: The Zones of Consumer Preference (from Jensen and Miller, 2007). Panel A (left) shows indifference curves for individuals with Standard consumption (red) and individuals with Subsistence consumption (blue). Individuals at the Subsistence level are extremely inelastic toward the Staple good, which gives rise to upward sloping demand.

The model presented here provides a precise reason for why the severity of poverty of poverty plays a large role in determining how a household will react to a price change. Specifically, it suggests that as income decreases, the individual's marginal value of an additional dollar in their budget constraint increases, which in turn means switching between unhealthy and healthy foods is less attractive than using that money for other, non-food, goods. Though not explicitly expressed in the model, another way to think about this behavior is that individuals become more inelastic towards the composite good as income decreases. Like food, there are other items the house can't live without, e.g. housing, water, etc.

Additionally, the model presented in this thesis explains the shape of the indifference curves that are exhibited by upward sloping demand (FIGURE 5 and FIGURE 6). It also describes the behavior as the result of the price differences between healthy and unhealthy

goods, and the relative preferences for each good, which is a more generalized take on food purchasing behavior compared to the Jensen and Miller approach.

In conclusion, given the dichotomy of outcomes from price interventions, it is first important to identify consumer preferences so that the price intervention will benefit society. Specifically, policy makers and researchers need to understand consumer preferences for certain products, and the willingness of consumers to switch away from those products at different price points. Furthermore, in addition to understanding preferences, it is vitally important to understand how income and calorie constraints interact with food preference and price, as these factors are strong determinants in whether a price intervention will be harmful or beneficial.

SECTION IV: EXPERIMENTAL DESIGN

This section investigates how food-purchasing behavior responds to different price interventions, namely taxes and subsidies, as well as investigates how those price interventions differentially affects individuals at different income levels. Though not a direct empirical investigation of the previous model, this section does provide a unique look at the interaction between purchasing behavior and price interventions. To investigate these questions, I utilize data from a field study that followed food purchases at two grocery stores over the course of nine months. In this field study, households were randomly assigned to a treatment group or control group, where the treatment group received a combination subsidy on healthy foods and tax on less healthy foods.

A. The Field Study

233 households who regularly shopped at one of two grocery stores of the same chain in the Northeastern United States were recruited to participate in a field study. The grocery chain had in place a propriety rating system for many of its food products, ranging from “Zero” to “Three”⁶. “Zero” was considered less healthy, and positive ratings were considered varying degrees of healthy, with “Three” indicating the most healthy food products. The rating system was based on a proprietary algorithm that gave higher ratings to products with more vitamins, minerals, fiber, and whole grains and lower ratings to products high in cholesterol, trans fats, added sodium, and added sugars.

Each participating household was asked to fill out a survey with family socioeconomic and demographic information, as well as individual characteristics such as age, weight, and

⁶ Seasonal products, and products with no calories did not receive ratings.

height. Recruiters were tasked with recruiting individuals (a) who did most of their shopping at the two grocery stores and (b) who did at least 75% of the grocery shopping for the household. This was to done to make the sample representative of grocery store purchasing behavior.

After the participant had completed the survey he/he received an ID card that was used to track their household's purchasing behavior over the course of the study. The cards worked as follows: at the checkout counter, the cashier would scan the individuals ID card, which would mark the to-be-purchased basket of items as part of the study, and would qualify the basket for the incentives that came with participating.

The recruiting took place in July of 2010. The data collection process began in August, after all of the participants were registered in a database that would track their purchasing behavior. Of the original 233, 11 did not properly fill out the initial form, bringing the number of active participants down to 222. Of the 222 active participating households, twenty households had more than one individual sign up for the study. In order to make sure the data was representative of household-level purchasing behavior, these multiple-participant households were merged into one household, which brought the total number of participating households down to 212. A baseline data collection period began for all 212 households in the beginning of August 2010. Each household during the baseline received a discount of 10 percent on all “Zero”, “One”, “Two”, and “Three”-rated items⁷. On September 7th to 9th, a little over a month into the study, households were randomized into either a control group or a treatment group. 53 were randomized into the control group, and 159 into the treatment group⁸. Households in the

⁷ Delineating between less health and healthy at the “Zero”-“One” margin was done because positively rated products (“One” and higher) were advertised as having good nutritional value. In retrospect, the margin could have been elsewhere, but a higher margin would have been more difficult to justify.

⁸ It should be noted that the treatment group has roughly three times the number of participants as the control group, which is because there were small differences in how the “taxes” and “subsidies” were framed. These differences were used in another study. For more information on the behavioral frame study, see Hanks, Just, and Wansink 2014.

control group continued to receive 10 percent off all purchases in the treatment period. On the other hand, the treatment group received the same 10 percent baseline discount off all food products during the baseline period but was taxed 5 percent for “Zero” rated items and received a 5 percent subsidy for positively rated items. This brought the effective price for “Zero” rated items to 95 percent of the original price, and 85 percent of the original for positive rated items for the treatment group. Given this formulation I can investigate the effect of the price intervention two ways: (1) within the treatment group - between the baseline and treatment periods, and (2) across groups – between the treatment group and the control group during the treatment period. This intervention period lasted from September 2010 until March 2011.

B. Scanner Data Panel

Purchase records were aggregated for each participant on a weekly basis. The data included information on expenditures, product price⁹, the health rating from “Zero” to “Three”, product descriptions, the time and date of purchase, and the participant’s unique ID number. At the end of the study, this data was brought together to create a panel of product-level observations for households for the nine months that it ran. Next, this panel was merged with household characteristic information that was obtained from the introductory survey. The survey information included employment status, income, education, marital status, number of household residents, and the race and age of the primary shopper.

C. Nutritional Data

⁹ Price differed from expenditures because of the incentives provided within the experiment, but also because participants could use coupons.

Separately from the scanner data collection, nutritional information was collected in order to investigate questions about the interaction between the price intervention and aggregate nutritional measures. The data provided by the grocery retailer included: a description of each product, the product's UPC code, and various classifications of the product. There were 16749 Product Names, which were broken into 24 Product Categories. In addition to the Product Category labels, the data were labeled with Family Names, 1020 unique in total. For example, boxed dry pastas were all part of the "Baking/Cooking" Product Group, but different varieties had different Family Names such as: "Short", "Long", "Baking Pasta", and "Healthy". Each product in the database was coded with one Family Name. See FIGURE 8 for a visual illustration of this process. There was an average of 16.42 products per Family Name. While that may sound like a lot, many unique Product Names were merely different sizes of the same product, so the summary statistics inflate the amount of diversity within each Family Name. That said, some groups did have many more products than others. Below is a table of the summary statistics, quintiles, and a histogram chart of the number of different Product Names per Family Name.


<u>Family Name</u>	<u>Product Description</u>	<u>Nutrition Information</u>
Popcorn Oil		
Pork Tenderloin	Banquet Pot Pie Turkey	
Portion Hams	Banquet Pot Pie Beef	
Portion Hams	Banquet Pot Pie Chicken	
Pot Pies	Marie Callender's Turkey Pot Pie	
Potato Chips	Marie Callender's Chicken Pot Pie	Nutrition Facts Serving Size 198 g Servings per Container 1 Amount Per Serving Calories 380.00 Calories from Fat 190.00
Potato Snacks	Willow Tree Chicken Pie	
Potatoes	Marie Callender's Parm. Chicken	
Potatoes, Bagged		
Potatoes, Bulk		
Potatoes, Organic		

Figure 8: Nutritional data collection process. Nutritional information was collected for a single representative product for each Family Name. For example, in the “Pot Pies” Family Name (left column), there were seven different unique products (middle column). One product was chosen at random to be the representative product. In this case it was “Banquet Pot Pie Turkey”. Once the representative product was randomly selected, nutritional information was collected for that product (right column), and was applied to every product in that Family Name.

Table 1: Overview of Representative Products.

Summary Statistics:	
N	1020
Mean	16.42
S.D.	23.4
Quantiles:	
Min	1
25%	3
Median	8
75%	20.5
Max	201

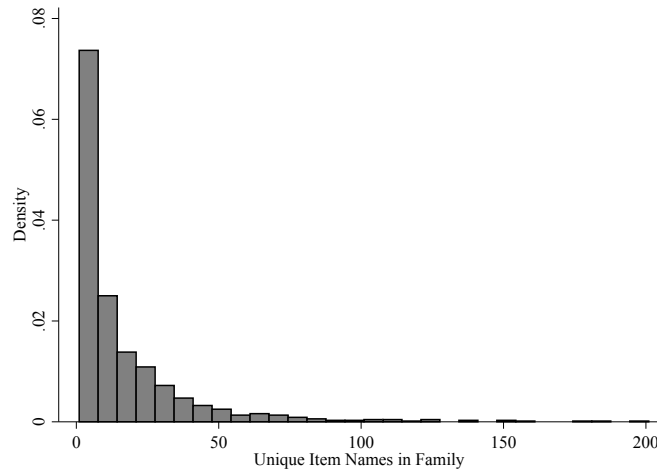


Figure 9: Histogram of Product Names Per Product Family. The right-skewed histogram indicates most Family Names had few products, but the long tail indicates there were a few Family Names that had a considerable number of unique products.

Given the large task of collecting data for 17,000 unique products, and given the little homogeneity in nutritional composition within product family, I decided to collect nutritional information at the Family Name level and apply that nutritional information to all Product Names within each Family Name. Since there could be more than one Product Name per Family Name, a product was chosen at random from each Family Name that would act as a Representative Product for that Family Name. 839 unique Representative Products were chosen¹⁰. Next nutritional information was collected for each Representative Product by looking up the product information in the grocery retailer’s online database of nutritional information.

All standard USDA nutrition was collected for each Representative Product: weight (or volume), Calories, Total Fat, Saturated Fat, Trans Fat, Cholesterol, Sodium, Carbohydrates, Fiber, Sugar, and Protein. All nutritional information was collected on a per-serving basis, which was either in grams, fluid ounces, or count (e.g. 1 ct. muffin). For foods that were not pre-

¹⁰ The number of Representative Products does not exactly match the number of Family Names because many produce items were classified under multiple Family Names depending on whether they were organic, conventional, pre-packaged, or bought in bulk. 100 g of an apple has the same nutritional content whether it was bought individually, in bulk, or was pre-cut and packaged.

packaged, namely meats, cheeses, and fresh produce, I used standard serving sizes of 4.00 ounces (113 grams) for meat, and 3.53 ounces (100 grams) for cheeses and fresh fruits and vegetables.

Next, I merged the nutritional data with the original scanner data panel. This was a one-to-many merge, where each Representative Product in the nutritional data set mapped to multiple product observations in the panel data set. After the merger, each product-level observation had serving size information, as well as the nutritional information for that serving size.

Most products contained multiple servings, so the per-serving data was not yet representative of total nutritional information. To calculate the total nutritional information in a given product, I multiplied the number of servings in a product by the per-serving nutritional information. To do this I first had to converting product weight (and volume) into standard weights (and volumes) – ounces for weight and fluid ounces for volume. To do this I used a Python script that matched the unit type in the original Scanner Data Panel to a standard weight (or volume) and then applied the correct conversion. For example, the script would take a volume in gallons, as identified by the labels (“GA”, “GAL”, or “GALLON”) and convert it to fluid ounces, where one gallon would become 128 fl. oz. With product sizes standardized, I proceeded to calculate total nutritional information by multiplying per-serving information by the number of servings^{11 12}. FIGURE 10 shows a breakdown of calories per serving in Representative Products by product rating. While there is no real difference between calories per serving between “Zero” and “One” rated products, there is a decreasing trend as the positive rating goes from “One” to “Two” to “Three”.

¹¹ There were a small number of observations that were not counted by weight or volume, but rather by quantity, and the formula for calculating calories per serving for these products was slightly different, but followed the same general procedure.

¹² It should be noted that this procedure systematically overestimates the nutritional content of some foods such as fresh produce, where a certain percentage of the weight of the food (hide, skin, peel) is never consumed.

Equation 3: Procedure for calculating total calories per product

$$\text{Calories Per Serving}_i = \frac{\text{Calories}}{\text{Serving size (in ounces)}} \text{ in RepProduct}_j$$

$$\text{Number of Servings}_i = \frac{\text{Product Weight}_i \text{ (in ounces)}}{\text{Serving size (in ounces)}}$$

$$\text{Total Calories of Product}_i = \text{Calories Ser Serving}_i \times \text{Number of Servings}_i$$

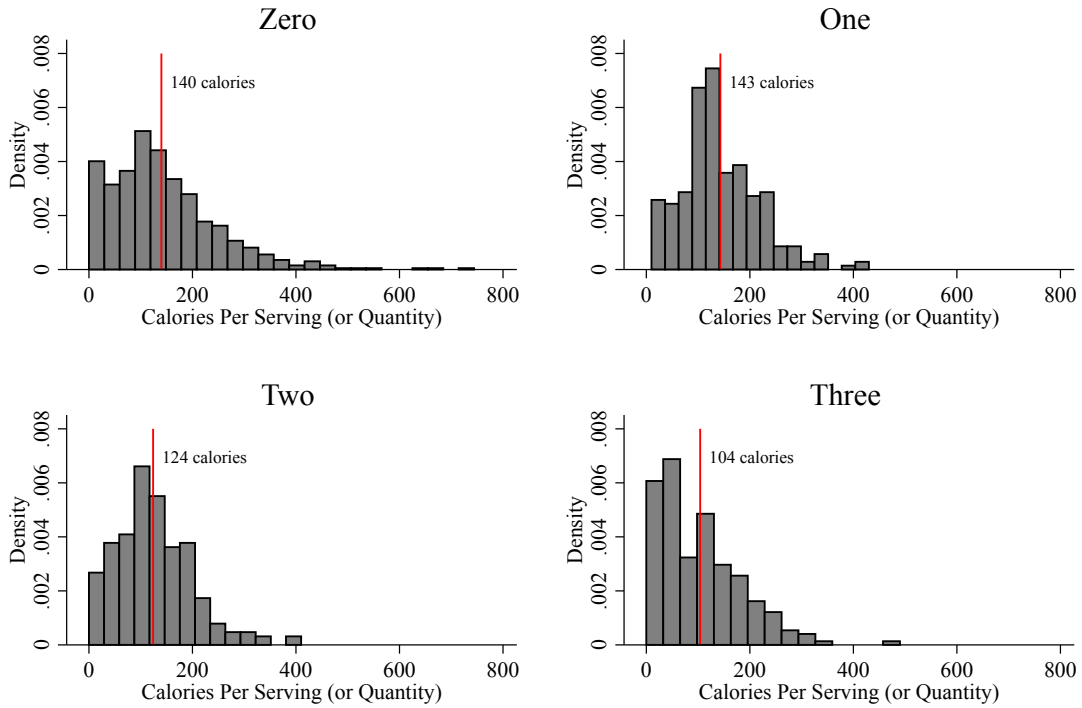


Figure 10: Calories Per Serving By Product Rating. Each histogram has nutritional information for a different product rating. The red line, and adjacent number, indicates the mean calories per servings for the products within a particular product rating.

D. Hypotheses

With the purchasing and nutritional data brought together, it was time to investigate whether or not households changed their purchasing habits from less healthy to more healthy foods. Analysis began with a descriptive overview of how the tax and subsidy affected different dimensions of purchasing behavior across all households. Next, a deeper analysis was done that looked at the effect of the treatment at different income levels.

Hypothesis 1:

Households in the treatment group will buy a greater proportion of healthy food in the treatment period relative to the amount bought by the control group. This hypothesis is in line the idea that households will rebalance consumption as to equate marginal utilities per dollar across healthy and unhealthy foods as response to the price intervention.

Hypothesis 2:

My second hypothesis is that some of the lower income households in the treatment group will react to the price intervention by buying a greater proportion of unhealthy foods. This behavior would parallel what the model predicts for individuals who prefer the money saved by not switching to healthy foods over switching to a greater percentage of healthy foods in light of the financial incentive.

SECTION V: EMPIRICAL STRATEGY AND RESULTS

A. Descriptive Overview of Data

Four variables were looked at to see if the pricing intervention had any effect on the types, quantities, and qualities of food purchased: (1) Total Calories¹³, (2) Weighted Expenditures, (3) Calories Per Weighted Dollar, and (4) the percentage of calories from positive rated – healthy – products, which I will refer to as γ -Cal.

Aggregating the Data

Despite having “product-shopping trip-household” level observations, for a majority of the analyses I aggregated the dependent variables over a four-week time period¹⁴. This was done to reduce irrelevant noise in the dependent variables of interest and to account for the fact that different households have different shopping frequencies – some households may go shopping multiple times a week, while others may only go every few weeks¹⁵. TABLE 2 provides summary statistics for the four dependent variables of interest.

¹³ 1 Calorie = 1 kilocalorie

¹⁴ At one-week and two-week levels of aggregation, there was considerable variation in aggregated variables that was resulted from differences in purchasing frequency and not necessarily purchasing behavior. The idea is that the higher up the data is aggregated, the more accurate portrayal of purchasing behavior will be over a given time-period. However, it should be noted that there is a direct tradeoff between the accuracy of the measurement and number of observations. Specifically, fewer observations can reduce power in statistical tests. In this case, the tradeoff is well balanced by the increase in legitimacy and accuracy of the measurement.

¹⁵ The primary reason this was done was to reduce measurement error for subsequent statistical tests and regression analysis. If there is measurement error in the dependent variables, so long as that measurement error is not correlated with covariates (the independent variables), the estimator will be unbiased and consistent. However, a problem will arise when making inferences from the data. Specifically, under the assumption of no autocorrelation, the estimated variance may be greater than the actual variance, which makes the statistics vulnerable to Type I error - improperly rejecting a true null hypothesis. Thus, it is important to be aware of this problem and mitigate it where possible. The most logical way to reduce measurement error in the dependent variables is aggregate to the variables over longer time periods. I investigated many time horizons, specifically day, week, two-week aggregations, and month, but every aggregation except month had considerable noise, which could increase the chances of finding a false

Table 2: Summary statistics for dependent variables.

		Mean	Std. Dev
Total Calories	(kcal)	127408	89084
W.Exp	(\$w)	366.15	254.87
Calories Per W. Exp	(kcal/\$w)	357.27	92.77
γ -Cal	(%)	39.8	12.2

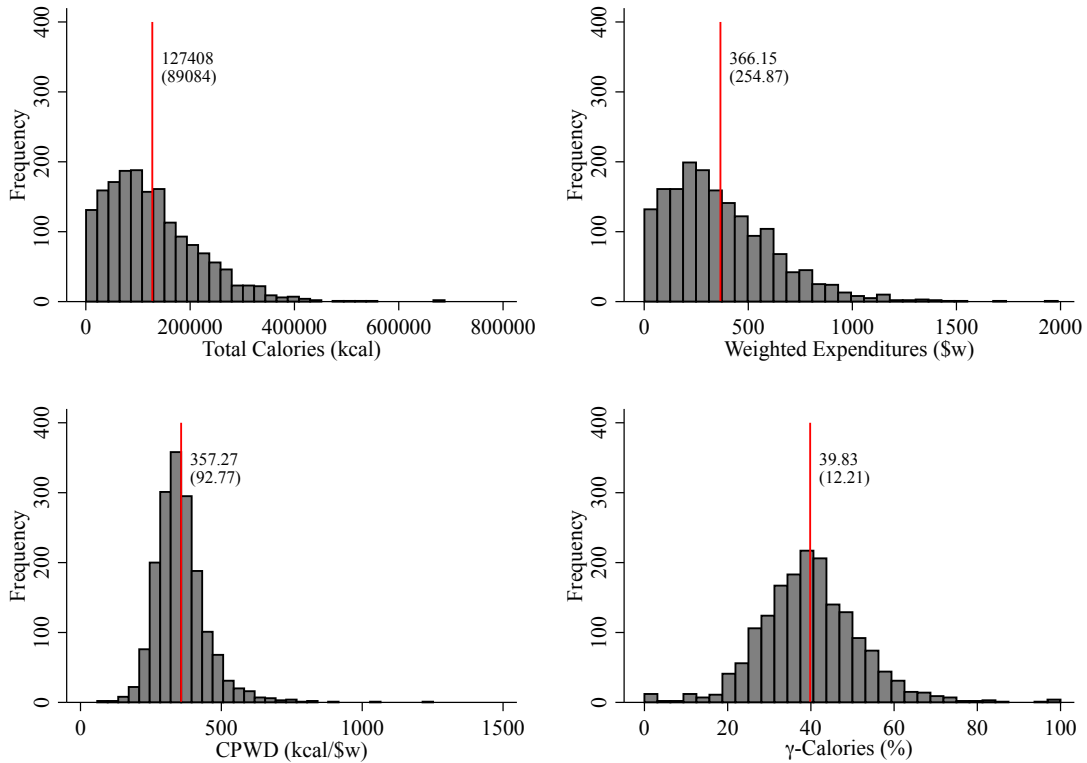


Figure 11: Dependent variables overview. These four graphs show the means, standard deviations, and distributions of the four dependent variables investigated. The red line and adjacent text indicates the mean, with the standard deviation below in parentheses. As can be clearly seen, the two distributions on the bottom are more normal than the two distributions on the top.

statistically significant result. The key assumption here is that food has to be consumed many times within a month, and therefore the consumption should smooth out over longer time horizons. Two people may or may not buy the same amount of kcal in one day, but over the course of a month they will likely buy similar amounts, and any differences will likely be able to be more easily controlled for with fixed effects.

i. Total Calories

The first measurement that was investigated was Total Calories_{tk}, which is the sum of the total calories in every product bought by Household_k in Month_t. This captures aggregate purchasing behavior for a household and can be influenced by a variety of factors including: the quantity of products purchased - more or fewer total products - or the composition of products - a shift towards higher calorie or lower calorie products. Even if the measure doesn't change over time, it may be because quantity and composition are moving in opposite directions. In order to see how households reacted to the treatment, purchasing behavior was investigate across all purchases as well as by ten different major Product Categories: Beverages, Breads, Dairy, Fruit and Vegetables, Meats, Dinners, Baking/Cooking, Cereals, Snacks, and Other¹⁶. Differences in the Total Calories_{tk} variable between the control and treatment group show how Total Calories changed as a result of the pricing intervention. Differences in Total Calories_{tkg}, where subscript g represents a Product Category g, will show whether there were any changes within and/or between any of the ten major Product Categories¹⁷.

FIGURE 12 shows means comparisons, assuming unequal variance, for households in the control Group and the treatment Group during the treatment period^{18 19}. On average there were

¹⁶ "Other" is an aggregation of 15 small product categories

¹⁷ The average Total Calories per household per month over the course of the study was 127,408 kcal, which based on a 2000 kcal per day diet can feed 2.12 individuals for a Month. 2.12 individuals is considerably less than sample average of 3.93 individuals per household. After taking into account the fact that, in 2009, about 32% of food was consumed away from the home, at places like work, school, or restaurants (Lin et al, 2012). Assuming the households in the study bought about 32% as well, then that would bring their total calories up to around 187,000 kcal, which is still low for how much it would take to feed a household of four for a month. There are a couple different explanations: (a) households in the sample did a disproportional amount of their food consumption away from the home, (b) households did all of their shopping at these grocery stores but did not always present their card that indicated their participation in the study; or (c) households purchased grocery items in other grocery stores.

¹⁸ Since households were randomized into control and treatment groups, it is assumed that their baseline behavior was the same and that any differences in the treatment period are a result of treatment itself.

¹⁹ Welch test (t-test assuming unequal variance) was used because although the two groups are sampled from the same population, it is not clear whether or not the households in the control and treatment groups would have equal

small differences across all groups, but for some product categories there were significant differences. The amount of Total Calories purchased in the “Baking/Cooking” category was significantly higher ($p < 0.05$) for the treatment group, while Total Calories from “Dinners” significantly lower ($p < 0.01$). Despite these changes, there were no significant differences in categories that policy makers might be most interested in, namely an increase in the Total Calories in the “Fruits and Vegetables”, and a decrease in Total Calories in the “Snacks” category.

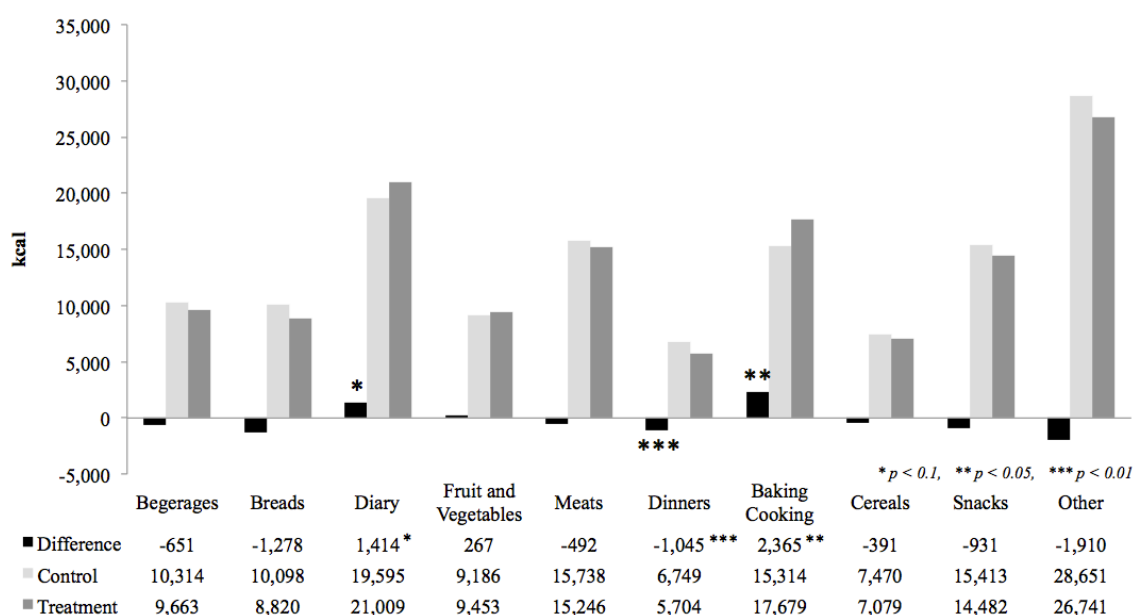


Figure 12: Total Calories means tests. This graph illustrates differences in monthly aggregated Total Calories within the ten different Product Categories. The “Difference” is calculated as the mean of the treatment group minus the mean of the control group.

ii. Weighted Expenditures

variances after the price intervention. Specifically, the treatment may cause households to change their food purchasing behavior in such a way that would increase or decrease the variance of the dependent measures; thus, ex-ante I decided to go with the Welch-test over the standard Student’s t-test.

Total Calories by itself provides a limited view of how households reacted to the treatment. To get a more complete view differences in Weighted Expenditures²⁰ were also investigated. Weighted Expenditures_{tk} was calculated as how much household_k paid in month_t paid for their food, net the incentive they received for the product being taxed or subsidized. If the household was in the control group, all products were discounted by 10 percent in both the baseline and treatment periods. On the other hand, households in the treatment group received a 10 percent discount on all products during the baseline period, and during the treatment period, less healthy products were “taxed” to bring the net discount to 5 percent, and healthy products were “subsidized” to bring the effective net discount on these products to 15 percent. Thus, weighted expenditures was calculated for the treatment group by household in the treatment group during the treatment period would only have to pay 85 percent of the original price of subsidized healthy good, but would have to pay 95 percent of the price of a “taxed” less healthy good²¹.

²⁰ USDA statistics for 2009-2010 indicate that about 51% of food expenditures are “food at home” purchases, with 49% consumed away from the home. The USDA also provides estimates at four Food Plans, each representing a different quartile of monthly food costs. One of the household size benchmarks for these Plans is a “Family of Four”. The average household size in this study was 3.93 individuals (adults + children), which is easily comparable to benchmark “Family of Four”. The “Thrifty Plan” (1st quartile), which is the national standard for a nutritious diet at minimal cost, was slightly more than \$500.00 in 2009-2010. The “Low-Cost” and “Moderate-Cost” plans, which reflect the 2nd and 3rd quartile respectively, were about \$650.00 and \$800 at the time of this study (USDA, 2009). The average monthly expenditure in this study was \$366.15, which at first glance is much lower than expected. However if you take into account that “food at home”, which is mainly grocery store purchases, was 51% of total food expenditures in 2009, than that would suggest the total food expenditures for households in the study was closer to \$717.65, a number squarely between the 2nd and 3rd quartile of monthly food expenditures for the nation (citation). Given there was about a 10% discount across the board, \$717.65 is probably an underestimate of true food expenditures for the average household. As discussed earlier, the average total calories purchased by households over the course of a month in this study was considerably lower than the national (50 percent vs. 68 percent), which suggests that households in this study are purchasing considerably more than the national average.

²¹ It is important to keep in mind that the treatment group was exposed to 10 percent discounts on less healthy food during the baseline period. One of the purposes of the baseline period was to give the households a chance to get used to the baseline discount. Therefore when the discount changed, the price intervention on the treatment group would have legitimate “tax” and “subsidy” effects, because the households had become accustomed to paying different prices.

Given Total Calories was not significantly different across many product categories, Weighted Expenditures can tell the story of how households were able to achieve that same level of calories. Was the balance achieved through less, or greater, expenditures?

To evaluate the effect of the treatment, I use the same means test as before, comparing the treatment group to the control group during treatment period. Results are summarized in Figure 11. In summary, there were no discernable differences across all products between the control and treatment groups. However at the product level, the treatment group spent more on Dairy ($p < 0.05$), and less on Breads, Dinners, and Cereals ($p < 0.05$).

The changes in Weighted Expenditures for Breads, Dinner, and Dairy are in line with the changes in Total Calories for those products. Specifically, households spent less on Breads and Dinners resulting in fewer calories from Breads and Dinners, and households spent more on Dairy, resulting in a greater number of calories from Dairy.

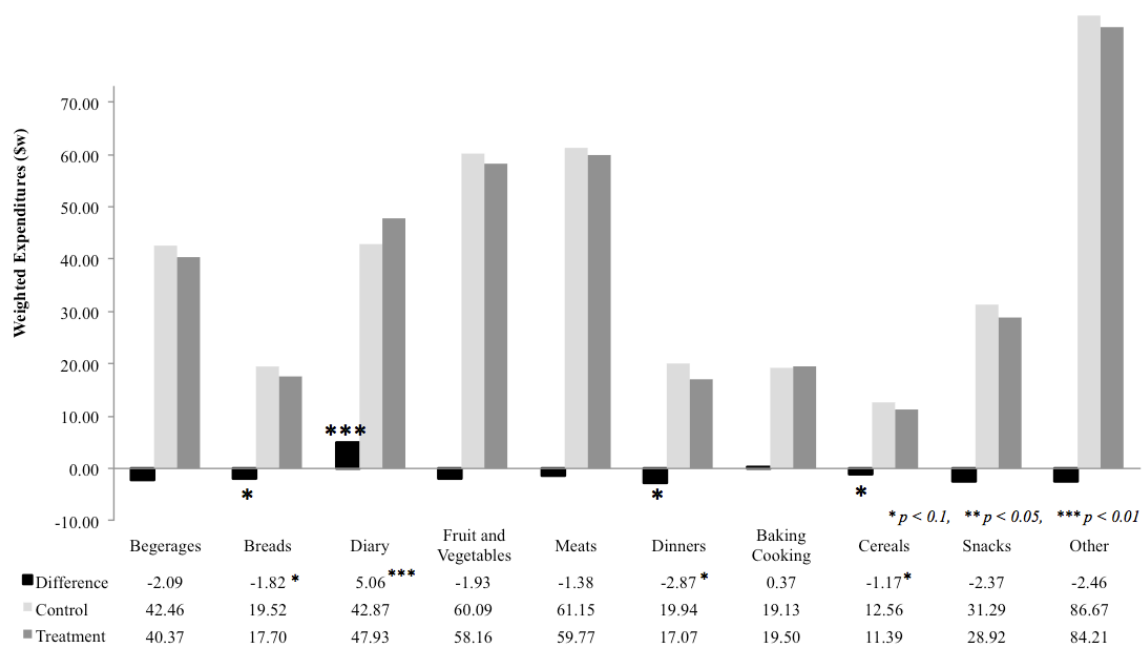


Figure 13: Weighted Expenditures means tests. This graph illustrates differences in monthly aggregated Weighted Expenditures within the ten different Product Categories. The “Difference” is calculated as the mean of the treatment group minus the mean of the control group.

Comparing the Weighted Expenditures data to the Total Calorie suggests that the volumes of some products - Breads, Dinner, and Dairy – changed as a result of the treatment ($p < 0.05$), but that the composition of the products did not significantly change, with the exception of dairy.

It should be noted that, similarly to Total Calories, Weighted Expenditures is a very noisy measure as some households do more food purchasing at grocery stores while others partake more in food away from the home. Thus, it would preferable to look at a measure (or measures) that reflect the core of what policy makers are interested in - the nutritional content of food – while still capturing differences in purchasing behavior.

iii. Calories Per Weighted Dollar

Calories Per Weighted Dollar (CPWD) is calculated by dividing Total Calories_{tk} by Weighted Expenditures_{tk}²². This new measure has two main advantages over the previously discussed variables. Firstly, it eliminates much of the noise that results from households having different purchasing behaviors. Households with small (or large) total expenditures will also have a small (or large) amount Total Calories. By taking the quotient of these two measures, the resulting calculation will be much more stable between households and across time. Secondly, it helps us understand the dynamics between Total Calories and Weighted Expenditures. Specifically, this variable captures the interplay of two variables between control and treatment groups. Referring back to the TABLE 2 and FIGURE 11, the ratio of the mean to the standard deviation is much smaller for Calories Per Weighted Dollar (0.26) compared to the same ratio for Total Calories and Weighted Expenditures (both 0.70). As discussed earlier, less noise in the dependent variable can translate to less estimated variance, which can decrease the likelihood of Type I error and can lead to more accurate inferences.

²² One of the motivations for this variable was the Drewnowski 2010 paper in which the authors discuss the nutritional value, nutritional density, and cost per dollar of various major USDA food groups. The paper discusses a relationship between the energy density (kcal/100g) and the price per calorie (\$/100 kcal), in which generally less healthy, energy dense foods (fats, oils, and grains) are cheaper per calorie on average compared to more healthy, less energy dense foods (fruits, vegetables, and meats). In his paper, Drewnowski presents a table with price measures, including “Energy cost”, which is measured as dollars per 100 kcal (Calorie). The statistics in the table reflect averages over 1387 foods from the Food and Nutrition Database for Dietary Studies and the Center for Nutrition Policy and Promotion food prices database. **Error! Reference source not found.** (top) presents Energy cost data for six food groups for which this data has clear comparisons.. By inspection, the means for various overlapping product groups are very similar: the mean Milk and Milk Products in the USDA data 434.78 kcal/\$ and in this study it is 455.45 kcal/\$, Fruit and Vegetables are 185.19 kcal/\$ and 147.06 kcal/\$ respectively, and the combined Fruit and Vegetables category in this study sits right in between at 171.78 kcal/\$. Overall, the fact that this the metric in this study so closely aligns with a metric calculated from a database provides robustness to this variable as a measurement.

Table 3: Comparison of Energy Cost Across USDA Food Groups

Drewnowski 2010			
USDA Major Food Group	Energy Cost		Calories Per Dollar kcal/\$
	\$/100 kcal	Std. Dev.	
Milk and Milk Products	0.23	0.13	434.78
Meat, poultry, and fish	0.41	0.31	243.90
Grain Products	0.14	0.1	714.29
Fruit	0.54	0.48	185.19
Vegetables	0.68	0.69	147.06
Sugars, sweets, and beverages	0.22	0.21	454.55
McGranaghan 2014			
Product Category	Energy Cost		Calories Per Dollar kcal/\$
	\$/100 kcal		
Dairy	0.22	-	455.45
Meats	0.38	-	264.88
Cereals	0.16	-	634.13
Baking Cooking	0.11	-	941.20
Fruits and Vegetables	0.58	-	171.78
Beverages	0.39	-	258.71

The CPWD means tests reinforce the differences found in Total Calories and Weighted Expenditures (FIGURE 14: CALORIES PER WEIGHTED DOLLAR). Breads, Dairy, and Dinners all show discernable decreases in CPWD between the treatment and control groups ($p < 0.05$), suggesting households in the treatment group purchased slightly more expensive calories of these products compared to the control group. Two interesting results were that CPWD decreases for Fruits and Vegetables and Baking/Cooking ($p < 0.05$). The difference in CPWD for Fruit and Vegetables can be explained by the fact that products in this category were mostly subsidized healthy items. Consequently households in the treatment group paid 5 percent less for these products compared to the control group. The price difference alone explains the difference

in energy cost between groups. The difference in Baking/Cooking cannot be explained by the same price effect that explained the difference for fruits and vegetables, as there is much more heterogeneity in product healthiness within the category. Thus, the likely explanation is that the treatment group bought cheaper calories (higher CPWD) in this product group compared to the control group.

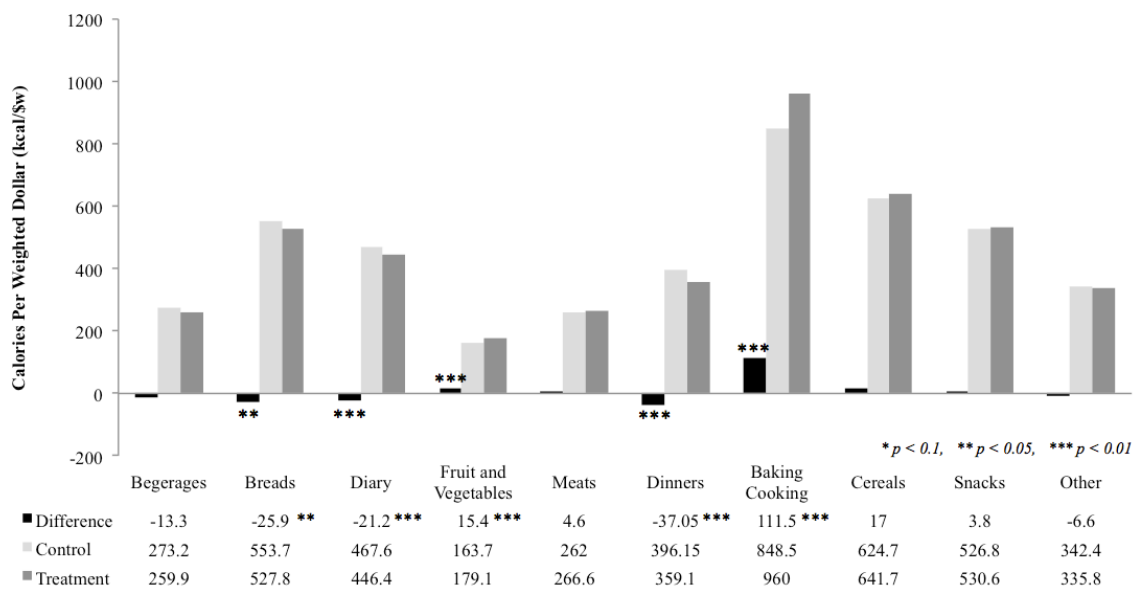


Figure 14: Calories Per Weighted Dollar means tests. This graph illustrates differences in monthly aggregated Calories Per Weighted Dollar within the ten different Product Categories. The “Difference” is calculated as the mean of the treatment group minus the mean of the control group.

iv. γ -Cal

The last variable I look is γ -Cal, which is the percent of calories from positively rated products. γ -Cal is calculated as the sum of Total Calories across all products with positive ratings divided by the sum of Total Calories across all positive and “Zero” rated products. Like Calories Per Weighted Dollar, γ -Cal can help explain what happens within product category.

FIGURE 15 presents the results. While there were no discernible differences between the treatment and control groups across all purchases²³, there were discernable differences within a few of the product categories. For categories such as Fruits and Vegetables, in which most products have positive ratings, it makes sense that the Treatment had little effect. However, for other product categories such as Dinners, Cereals, and Snacks, which are not saturated by healthy products, the data suggest the price intervention may have had a positive effect. Explicitly, γ -Cal was significantly higher in the treatment group for Breads, Dinners, Baking/Cooking, Cereals, and Snacks ($p < 0.05$). Only in the Dairy product category did the treatment group consume significantly more calories from less healthy foods ($p < 0.05$).

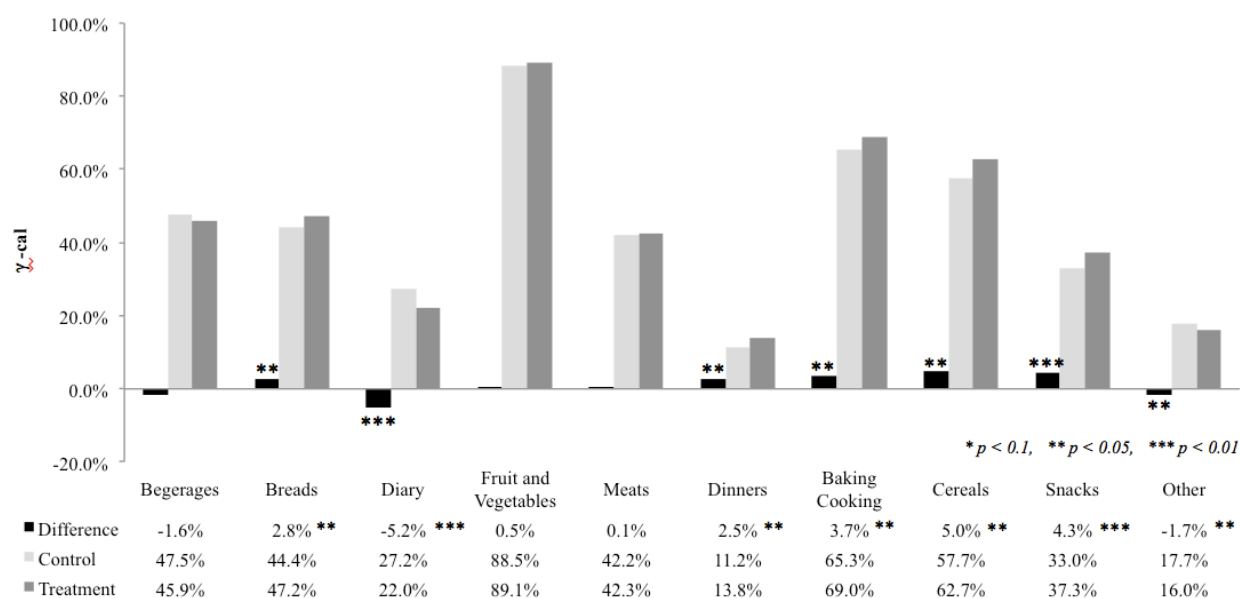


Figure 15: Percent of calories from healthy foods means tests. This graph illustrates differences in monthly aggregated γ -Cal within the ten different Product Categories. The “Difference” is calculated as the mean of the treatment group minus the mean of the control group.

²³ The difference between γ -Cal between treatment and control was very close to being significant at the 10 percent level.

To summarize, while households in the treatment group for the most part did not change the total amount of calories bought, or change how much they spent, they did seek out a greater percentage healthy products. Furthermore, despite the fiscal intervention not encouraging significant increased consumption of key healthy categories such as fruits and vegetables, it did seem to encourage individuals to make switches to healthy products within certain product categories.

Despite the attractiveness of these conclusions, they may be premature as the means tests suffer from many limitations. Firstly, they don't control for various household-level fixed effects that could be driving the differences between treatment and control groups. Though this shouldn't be a problem because of the randomization, the possibility exists that difference in household make-up were key contributors to the significant differences. Furthermore, the time periods may be contributing to increased variation in the treatment or control groups, which could be affecting the measurement accuracy of the dependent variables and thus influencing the legitimacy of the statistical inferences. A logical way to correct for these unwanted sources of variation is to control for them. Controlling for these household and time fixed effects should reduce the noise in the dependent variables of interest, which increase the accuracy of the analysis of the effect of the treatment.

B. Regression Analysis

In order to isolate the effect the price intervention had on the treatment, I used linear regression analysis to control for time-invariant household fixed effects and time fixed effects. Given households were randomized into treatment and control groups, the control group in the

treatment period provides a counterfactual for what how the treatment group would have behaved if it never received the price intervention²⁴.

Equation 4: Model: Base Specification

$$Y_{kt} = \beta_0 + \beta_1 TxGroup_k + X_k \eta_j + Month_{t'} \alpha_{t'} + \varepsilon_{kt}$$

Equation 5: Cluster robust variance calculations

$$VAR_{C.R.} = (X'X)^{-1} \sum_{j=1}^{N_c} \left[\left(\sum_{j_c} e_i * x_i \right)' \left(\sum_{j_c} e_i * x_i \right) \right] (X'X)^{-1}$$

The first model is a cluster robust Ordinary Least Squares model that takes into account household level fixed effects and time fixed effects. Clustering at the household level allows correcting for intrahousehold correlation within the data, and specifically the issue that less unique information is provided for each additional household measure. Y_{kt} refers to the dependent variable being estimated for household \mathbf{k} in time period \mathbf{t} ²⁵; β_0 is a constant; $TxGroup_k$ is a dummy variable indicating whether or not the household is part of the treatment group; $Month_{t'}$ is the month of the observation, X_k is a vector of \mathbf{j} fixed effects for each household \mathbf{k} and ε_{kt} is the error term²⁶. The coefficient of interest is β_1 , which captures the difference in the regression-controlled dependent variables of interest between the control and

²⁴ A difference-in-difference model, which would control for noisy differences in the groups during the Baseline period, was considered, but significantly decreased the power of the statistic.

²⁵ t' , as compared to t , only includes months during the treatment period

²⁶ Household fixed effects include: age, household income, household size, household race, education, employment, BMI, and marital status.

treatment groups. This specification is used estimate Total Calories and Calories Per Weighted Dollar across all product categories, as well as by individual product category²⁷.

For Total Calories, there were no discernable differences between the control group and the treatment group across aggregate purchases or by any individual product category. Thus, once covariates were parsed out, the treatment had no apparent affect (top panel of TABLE 6: TOTAL CALORIES REGRESSIONS). For Calories Per Weighted Dollar (CPWD), there are some differences between the control and treatment group. As was the case in the means tests, the significant difference between the treatment and control group was likely due to the price differences for these products and not due compositional changes in the types of products purchased²⁸ (top panel of TABLE 7). Based on these regressions, and these regressions alone, there was no significant effect of the combined subsidy and tax treatment on total calories purchased in total, and within separate product categories.

C. Poor Interactions

Food-purchasing behavior is an important issue in many American households, and as discussed in the introduction there are some households that will be more seriously impacted by a tax or subsidy than others. Lower-income households, who spend a greater proportion of their total expenditures on food, may be more seriously impacted by food taxes or subsidies. These

²⁷ These were not stacked (seemingly unrelated) regressions, but separate regressions run of distinct subsets of the data. Stacked regressions could have been used to take advantage of the fact that the error terms were likely correlated across product category regression equations.

²⁸ To illustrate, consider the case of fruits and vegetables. The control group received a 10% discount on a majority of these products (~89% were healthy), while the treatment group received a 15% discount. Combine this 5% price differential with the fact that fruits and vegetables had an average CPWD of about 170 kcal per dollar, then if purchasing behavior did not change between the two groups, one would still expect to see a about a 10 kcal difference between CPWD for the treatment group and the control group as a result of the denominators being different. An analogous story can be told about the Dinners category. Specifically, the 41 kcal per dollar decrease in CPWD is very close to what one would expect if purchasing behavior did not change. The average CPWD for Dinners was about 900 kcal, and 5% of that is 45 kcal. Thus, assuming purchasing behavior did not change, one could still expect CPWD to differ by about 5% or 45 kcal between the treatment and control groups.

households may also be calorie constrained, in which case changing the price of food may drastically change their overall utility level and percentage of healthy food in the desired, or undesired, direction from a policy point of view.

In order to look at how the price intervention affects individuals at different income levels, a dummy variable is defined, “Low-Income”, in the dataset that indicates whether or not the household could be eligible for SNAP benefits using 2009 Poverty Guidelines for the 48 Contiguous States and the District of Columbia²⁹. Households were classified as “Low-income” if any part of their income bracket, obtained from the initial survey, fell below 130% poverty threshold given the number of individuals in the household, also obtained from the initial survey^{30 31}. TABLE 4 shows the cutoffs for different household sizes. To give an example, a four-person household with an income in the \$20,000 - \$30,000 bracket would be considered “Low-Income” by this definition, whereas a two-person household in the same income bracket would not be considered low-income. TABLE 5 provides a breakdown of household characteristics across the whole sample as well as broken down by poverty status.

²⁹ The U.S. Department of Health & Human Services provides guidelines every year.

³⁰ This definition of Low-income is conservative in the sense that it includes individuals who might not below the 130% poverty threshold for their income and family size. This was done because households just above that margin likely exhibit behavior closer to low-income households than high-income households. Essentially, this was done in order to avoid misclassifying any households as “High-income” that were actually below 130% of the poverty level.

³¹ 130% was chosen as the cutoff because that is the cutoff for SNAP benefits.

Table 4: 130 Percent Poverty Thresholds by Household Size, 2009

Household Size	130% of the Poverty Line
1	14,079
2	18,941
3	23,803
4	28,665
5	33,527
6	38,389
7	43,251
8*	48,113

* 3,740 for each additional person above 8.

Table 5: Household Characteristics By Poverty Status

	Poverty Status		Total
	Low-Income	Higher-Income	
Education			
Pre BA	53	24	77
BA	44	12	56
Graduate	66	2	68
NA	11	0	11
Employment			
Homemaker	46	13	59
Part/Un/Ret	11	11	22
Full	106	14	120
NA	11	0	11
HH Size			
1 or fewer children	66	10	76
2 or more children	108	28	136
HH Income			
10k-40k	15	38	53
40k-70k	56	0	56
more than 70k	82	0	82
NA	21	0	21
Marital			
Married	142	23	165
Not Married	21	14	35
NA	11	1	12
Race			
White	156	35	191
Other	16	2	18
NA	2	1	3
BMI Status			
BMI < 25	87	21	108
BMI ≥ 25	87	17	104
Total	174	38	212

In order to understand the causal effect the price intervention had on lower income households, difference-in-differences estimation was used. Difference-in-difference estimation gives robust insight into the causal effect of the treatment on lower income households by controlling for the effect of being in the treatment group, the effect being lower income, and the combined effect of being lower income and in the treatment group. The model is as follows:

Equation 6: Model – Lower Income Interactions Specification

$$Y_{kt} = \beta_0 + \beta_1 TxGroup_k + \beta_2 LowIncome_k + \delta_1 (TxGroup_k \times Poor_k) + Z_k \lambda_l \\ + Month_{t'} \alpha_{t'} + \varepsilon_{kt}$$

In this specification β_0 is a constant; β_1 controls for differences between the treatment group and the control group; β_2 controls for differences between lower income individuals and higher income individuals. $TxGroup \times Poor$ is the interaction of $TxGroup$ and $Poor$, which equals 1 if the household is both low income and in the treatment group; δ_1 is the difference-in-difference estimate on this variable and controls for differences between lower income households in the treatment group and lower income households in the control group. Essentially, it provides an estimate of how the treatment effect on lower income households. $Month_{t'}$ is the month of the observation in the treatment period; and Z is a vector individual level fixed effects^{32 33 34}.

³² The fixed effect vector Z is different than X in the original model in that Z no longer includes a fixed effect for income as that is captured by the highly correlated with the new Low-income variable.

³³ Households were randomized into treatment and control groups, which should lead to each group having similar attributes, and therefore any difference in outcome will be a result of the treatment and not differences in characteristics.

Equation 7: Difference-in-Difference Coefficient:

$$\hat{\delta}_1 = ((\overline{Y_{kt}}|Tx = 1, P = 1) - (\overline{Y_{kt}} | Tx = 1, P = 0)) \\ - ((\overline{Y_{kt}}|Tx = 0, P = 1) - (\overline{Y_{kt}} | Tx = 0, P = 0))$$

Estimating Total Calories using the Low-income interaction specification yielded no significant differences between the control and treatment groups. Furthermore, as evidence by the lack of significance on the in the difference-and-difference estimate, there appear to be no differences between the lower income households in the treatment group and lower income households in the control group. The there was one significant difference (at the 10% level) in Total Calories in the Snacks product category, which suggests lower income households in the treatment group may have purchased a greater number of calories from snacks than lower income households in the control group.

Table 6: Total Calories Regressions

Product Category	All	Beverages	Breads	Dairy	Fruit and Veg.	Meats	Dinners	Baking/Cooking	Cereals	Snacks	Other
Base Model											
TxGroup	-3309.0 (10656.5)	-784.1 (1015.1)	-1358.9 (963.0)	861.6 (1908.5)	266.5 (907.3)	-462.6 (1576.0)	-1139.0 (628.0)	2186.0 (1777.6)	-126.2 (625.0)	-1044.3 (1577.6)	-2417.5 (2591.8)
Low-income Interactions Model											
TxGroup	-6536.5 (12639.2)	-829.4 (1171.4)	-1648.3 (1122.3)	31.6 (2174.4)	-19.8 (1016.3)	-812.5 (1787.1)	-1391.8 (740.0)	1956.1 (2102.9)	-540.1 (729.8)	-1758.9 (1860.3)	-3427.4 (3169.6)
Low-income	-38277.5* (17661.6)	-1875.8 1820.1	-3080.5* (1495.2)	-7583.2* (2918.3)	-2080.9 (1764.9)	-4676.0 (3040.8)	-2087.5 (1226.8)	-2818.0 (3363.0)	-2001.8 (1223.9)	-7073.0** (2337.4)	-11115.6** (3979.4)
TxGroup x Low-income	20769.3 (20894.7)	356.0 (2184.3)	1705.3 (1701.5)	4427.7 (3703.0)	1459.6 (2001.7)	1783.4 (3609.5)	1362.7 (1469.4)	2127.5 (3951.2)	2046.4 (1519.1)	4237.2 (2738.4)	6527.5 (4798.5)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

³⁴ An alternative would be to do a difference-in-difference-in-difference that also included observations from the baseline timeperiod - observations from before the treatment. This triple diff approach would also allow me to control for differences between the baseline period and the control period, at the cost of many degrees of freedom. Since households were randomized into their treatment groups, I feel safe in excluding the baseline observations from the regression analysis.

Similar results were found for the Low-income interaction specification of the model with CPWD as the dependent measure. There were no discernable differences between the control or treatment groups across all product categories and only one discernable difference at the product category level, within the Dinners category. This significant interaction suggests Low-income facing a tax and subsidy decreased their energy costs in this category by either increasing their calories more than then increased their costs, or decreasing their calories less than they decreased their costs.

Table 7: Calories Per Weighted Dollar Regressions

Product Category	All	Beverages	Breads	Dairy	Fruit and Veg.	Meats	Dinners	Baking/Cooking	Cereals	Snacks	Other
Base Model											
TxGroup	6.8 (9.8)	-13.3 (17.3)	-24.9 (21.1)	-25.5 (15.2)	15.5* (7.0)	6.9 (10.5)	-41.0* (18.6)	96.0* (44.0)	17.2 (23.9)	9.5 (17.5)	-3.4 (12.7)
Low-income Interactions Model											
TxGroup	4.7 (10.1)	-19.0 (18.8)	-18.3 (21.8)	-27.7 (17.1)	12.6 (8.0)	13.3 (10.9)	-55.7** (21.0)	95.9 (49.3)	15.8 (26.8)	14.0 (19.6)	-8.8 (13.3)
Low-income	5.5 (27.4)	2.7 (44.4)	-0.9 (60.1)	-12.5 (32.4)	-6.0 (16.1)	36.1 (29.7)	-73.6 (39.2)	32.9 (97.8)	0.8 (67.7)	25.9 (45.5)	-7.6 (33.8)
TxGroup x Low-income	7.7 (30.1)	28.2 (51.8)	-47.4 (62.0)	14.8 (39.5)	5.5 (19.4)	-36.1 (32.3)	84.1* (42.4)	16.4 (111.3)	3.7 (73.8)	-27.4 (50.6)	21.5 (39.2)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D. Discussion and Limitations

Based on these results, and these results alone, one would fail to reject the null hypothesis that a combined subsidy and tax has a significant effect on the total number of calories across all products or the composition of those calories. Though the treatment did have a significant effect within a few product categories, there are aspects of the data and specifications of the statistical tests that may be clouding a significant treatment effect.

Firstly, and probably the most serious limitation of this study is the possibility that the generalization of nutrition information on the product level masked actual differences in purchasing behavior. Specifically, the nutritional data collected at the Family Name level might not be reflective of the actual nutritional content in all the products within a particular Family Name. It is possible that the nutritional information collected for each representative product drastically overestimates or underestimates the actual calorie content in the food, or both, which would cloud the results and consequential inferences. For example, consider the hypothetical Family Name “Sliced Bread”, which has two hypothetical products: “Healthy Sliced Bread” and “Less Healthy Sliced Bread”, and that “Healthy Sliced Bread” was randomly selected to be the representative product for its Family Name. Now suppose that all households in the baseline period bought “Less Healthy Sliced Bread”. Furthermore, presume all households in the control group continued to buy the less healthy variety in the treatment period, whereas households in the treatment group made the switch to the healthy variety. The end result would be a very real difference in purchasing behavior that was not adequately captured by only one representative product. One way to fix this would be by increasing the detail of the nutritional data. Ideally one would want exact nutrition data on all products, but another, more manageable, way may be to collect nutrition data for a product at every product level (“Zero”, “One”, “Two”, and “Three”)

within each Family Name. This would provide a more granular, and thus clearer and more representative, picture of how purchasing behavior reacted to the fiscal intervention.

Another limitation of this analysis is that it only provides a limited picture of food purchasing behavior. As mentioned before, on average about 50 percent of food expenditures, and only 30 percent of calories are purchased, outside the household, which means this study looked at less than half of the whole picture. Thus, the results should be generalized with caution. Specifically, even though households in the treatment group tended to increase the proportion of total calories from healthy food, their purchasing behavior away from home might have gotten less healthy, which could have partially or fully negated any positive effects from the subsidy and tax. The only way to address this would be to have a more complete picture of food purchasing behavior outside the home, which is a very important, but difficult task given the decentralized nature of food purchasing behavior away from the home, i.e. households, and the individuals the comprise them, buy food at many different places: school and work cafeterias, restaurants, markets, sporting events, etc.

Similarly to the idea that households in the treatment group switched to less healthy foods away from the home is the idea that households switched foods that were labeled as less healthy to foods that were labeled as healthy, even though the healthy labeled weren't any more healthy, i.e. they found some nutritional arbitrage. This could arise for a few reasons. Firstly, since not every single product was labeled ("Zero", "One", "Two", or "Three"), households in the treatment group could avoid paying tax on a particular food if they found a similar food that had no product rating. Another possibility is that households gamed the nutrient ratings. Specifically, they could have made changes from a less healthy to a more healthy food at the margin for one product, while simultaneously buying a much less healthy variety of another product. To

illustrate, consider a hypothetical household in the treatment group that buys two unhealthy foods during the baseline period: (1) vanilla ice cream and (2) fried potato chips. In the treatment period the household switches from less healthy fried chips to a healthier baked variety instead of their usual fried variety. However, instead of buying plain vanilla ice cream they buy peanut butter cup brownie ice cream, which is considerably less healthy than the previously purchased plain variety. In the end the household ends up purchasing more healthy products, but the overall nutrition profile may be no better, and may even be worse.

Another limitation of the data is that it is limited to one region in Northeastern United States, which means the results may not generalize to the entire U.S. population. For example, Caucasian households were over-represented in the household compared to national averages, which may lead to different coefficient estimates compared to similar estimates derived from a nationally representative sample. This limitation could be addressed by using larger, and more nationally representative, panels of food purchasing behavior at home. One way to develop such panels would be for researchers to work with national grocery stores and food retailers in a combined effort to help consumers with their food purchasing decisions.

In addition to limitations in the data there are also limitations in the statistical methods employed. One such limitation is the potential misspecification of the regression model. Specifically, the model may not be taking into account some important nonlinearities, or it may be omitting relevant variables, which means the resulting estimates may be biased and/or inconsistent. I performed a Ramsey Regression Equation Specification Error Test (RESET) test on the base regression for total calories ($F(3, 1257) = 11.14, p < 0.01$) which indicated that non-linear combinations of the explanatory variables may help in explaining household total calorie purchasing behavior. This means that, in its current form, the model would benefit from raising

some of the explanatory variables to higher powers. To fix this, I could run different specifications of the model with different non-dummy variables raised to higher powers. This could improve legitimacy of the model, and in particular reduce the bias and increase the consistency of the estimates it produces.

Another way this misspecification can be seen is in the behavior of the standard errors, and specifically the difference in standard errors with and without clustering by household. Precisely, standard errors were decreasing as the result of clustering, which suggests there was negative intra-household correlation. This behavior suggests considerable variation within and between households that is inadequately captured by the model.

Notwithstanding these limitations, the present research shows that a combined tax or subsidy had little effect on household purchasing behavior. The price intervention was large enough to incentivize change within a few product categories, but was not large enough to significantly change purchasing behavior on the aggregate or within in important health-related categories such as fruit and vegetables.

SECTION VI: CONCLUSION

A. Theoretical model

Though the law of demand is very intuitive, it may not hold in all situations. As this paper illustrates one such situation is when lower income households are calorie constrained and face price differences between healthy and less healthy foods. Specifically, the model shows that lower income households who are calorie constrained can have upward sloping demand for less healthy products due to the households tight budget constraint and preferences for, and the relative prices of, healthy food, less healthy food, and a composite good. From a policy point of view, this means that if a tax were implemented on unhealthy food, with the purpose of decreasing consumption of that unhealthy food, there would be some lower income households who increase their consumption from unhealthy foods. This outcome is very undesirable, especially since the negatively affected households are some of the most vulnerable. In light of these results, policy makers need to be very careful when formulating price interventions, and should judiciously look at not just own-price elasticities across the general population, but own-price elasticities at different income levels as well as cross-price elasticities between different food groups in order to get a holistic assessment of the potential impact of a tax.

B. Empirical Models

The results of the various empirical assessments - means tests, the base model, and the interaction model - indicate that the combined tax and subsidy produced few detectable differences between the treatment and control groups and between lower-income households in the treatment group and lower-income households in the control group.

Firstly, there were no changes in purchasing behavior across the all purchases for each of the dependent measures - total calories, weighted expenditures, calorie cost, and the proportion of calories from healthy food. In terms of the total calories purchased by households, even though the means tests indicated a few significant differences between the treatment group and the control group within certain product categories, the regression-controlled differences were not significant. Furthermore, while there were some significant changes in expenditures, these changes were not clearly identified as the result of the treatment, but instead may be been the result of the design of the study. The one measure that did show a promising effect of the treatment was γ -Cal – the percentage of calories from healthy (positively rated) products within a few of the product categories.

Despite positive changes in the proportion of calories from healthy products, there was no evidence that households switched from less healthy product categories to more healthy product categories. For example, there was no shift towards fruits and vegetables, a category that policy makers and health specialists would like to see a positive change in. Bringing these findings together suggests that individuals in the treatment group, who were incentivized to buy healthier food and dis-incentivized to buy unhealthy food sometimes made switches to healthier varieties when the option was available, but did not make an extended effort to switch between product categories; and when changes were made, there were not significant caloric differences between the healthy and less healthy varieties.

These empirical findings suggest a modest, if any, effect of fiscal policies on purchasing behavior. Despite not directly influencing behavior, these price interventions can still greatly benefit society. Given the relatively small change in purchasing behavior in face of a tax, these taxes can be used to raise a substantial amount of revenue. Extrapolating the 5 percent tax from

this study to the general population would result in around \$10 billion ³⁵in tax revenue, which could be used for food and/or health related research, education, and even food subsidy programs.

³⁵ Estimated by summing 5 percent of total expenditures (pre-weighted expenditures, not to be confused with weighted expenditures) on “Zero” rated products in the treatment group during the treatment period, which gave an estimate of the total revenue from the six-month treatment period of the study. That number was then multiplied by 2 to get a yearly estimate, and then divided by number 625 (159 households at 3.93 individuals per household), an approximate of the number of individuals in the treatment group. The result was an estimate of how much the average person would be taxed in a year, which I multiplied by 317 million, the most recent estimate of the population of the U.S. (quickfacts.census.gov). This is a very rough approximation, but gives an idea of the potential magnitude of tax revenues.

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